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Analysis of data from drones for surveillance and threat identification in maritime areas

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"Analysis of data from drones for surveillance and threat identification in maritime areas"

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Introduction

Innovative and functional AI Drones (Artificial Intelligence Unmanned Aircraft) systems, commonly known as 'drones', have revolutionized fields such as civil protection, maritime and land surveillance, natural disaster management and threat monitoring in public spaces. More than ever, drones are coming into our daily lives to improve public safety in search and rescue, to identify important information from digital images, video and other visual inputs to take action and increase efficiency in saving lives. . One of the most important applications of drones is in maritime and land surveillance and threat identification, they are used to monitor vast sea areas, detect criminal and criminal activities and prevent any incident in maritime areas. These drones have the ability to move more efficiently than traditional surveillance methods in a short amount of time. In addition, drones equipped with high-resolution sensors and thermal cameras can detect threats such as illegal fishing, oil spills, drownings, lifeboats and other public hazards.

There are many benefits to drones playing key problem-solving roles in various fields such as maritime security, but there are also some individual limitations. One of the most basic constraints is the regulations surrounding the use of smart UAVs (Unmanned Aerial Vehicles). In some areas, their use is restricted and requires special permission. In fact, smart UAVs are particularly popular that use artificial intelligence (AI) in real time, allowing rapid data analysis, recording of the marine space which thanks to the artificial intelligence software can perceive the incident, identify objects and provide real-time analytical feedback processing. Artificial intelligence UAVs (Unmanned Aerial Vehicles) commonly known as "drones" research their approach, helping with positive results in the coordination of prevention of dangerous situations and the mission of search and rescue.

Keywords: Artificial Intelligence, Smart UAV, Real-Time, Object Detection, Deep learning.

Related work

Nowadays, the use of the camera mounted on each UAV-drone for identification and surveillance has brought a great development in the field of security and protection. Many real-time tracking applications from UAV-drone images or videos are in circulation. Below, comprehensive implementable methods of tracking objects, people and vehicles in recent years are presented.

In the online article "Real-time detection of people and vehicles from UAV images" (Reference 21), the thermal camera detection method from UAV-drone real-time detection of vehicles and people is presented. Vehicle detection is based on multi-level trained cascaded Haar classifiers, while detection is done using a thermal camera rendered on a real image. Similar detection models are achieved for the detection of individuals. Detection success rates are around 70% for people moving in real time, while vehicle rates are around 80%. Remarkable is the fact that in each flight of the UAV-drone the total percentage reaches 90%. In the implementation of the application, the sampling is done at a rate of 1 fps in order to get the best image from the thermal camera of the UAV-drone. The main difference in detecting a person or a vehicle is its size. It is more noticeable to detect a large vehicle than a person who often due to low contrast is not easily perceived. Solving this problem is its thermal cameras. They greatly improve the initial state of the image, but the problem is still evident due to unpredictable weather phenomena that prevail in any case and affect the image from the thermal camera of the UAV-drone.

In addition to person and vehicle detection, they are also processed as a confidence index for each person or vehicle detected. This information can help as an input to some other secondary control system with an emphasis on the easier classification of the results and their further investigation. Thus, the increased accuracy is achieved by using multiple classifiers and sensors manned by the UAV-drone.

The control system used to capture images from the unmanned UAV-drone which includes an optical and thermal camera. It is set to fly above 60 meters in altitude, with the thermal camera pointed at the ground at an angle of 45 degrees, creating a distance to the target in a straight line of 180 meters. The received images are sent to the information center through the radio receiver and the processing of the detection is carried out on a quad-core Intel processor with an operating frequency of 2.33 GHz.

In conclusion, the person or vehicle detection routines use a pair of images, an optical image and a thermal one. In the first phase, the two images are processed individually and then their information is extracted in combination for the final result. For vehicle detection from visual image, the test is performed with different multiple cascaded Haar classifiers trained for vehicle detection in different directions and illumination. After detecting a vehicle with all the above models, this specific point of the image is also checked in the corresponding thermal image. Locating a person is achieved in a similar way. It should be emphasized that the confidence index will increase more if the point where the contour is placed resembles the Gaussian model and the point exists within the corresponding detection area.

In this e-article "Integrated real-time object detection by a UAV in the warning system" (Reference 22), real-time detection detection of any moving object and person recorded by the UAV is presented. The detection is done with YOLOv2 algorithm which is aimed at an emergency warning system. This algorithm is executed on a GPU with low power requirements so that it can also be executed on mobile devices such as (smartphones, mobiles, tablets). Allow enough images or video as a data stream to process and forecast accuracy to trigger the emergency warning system that take place in real time. Aerial flights by the UAV collecting images or videos can pinpoint the possible locations of an emergency such as a fire outbreak in real time. It can also help locate people trapped by fire, search for missing people and rescue them. The design here is to locate and manage the emergency system notification. All implementation is done "onboard" so there is no risk of data loss in a potential wireless connection. A GPU camera has been installed on the UAV, which detects the image or video in real time with a very good ratio of accuracy and fps speed.

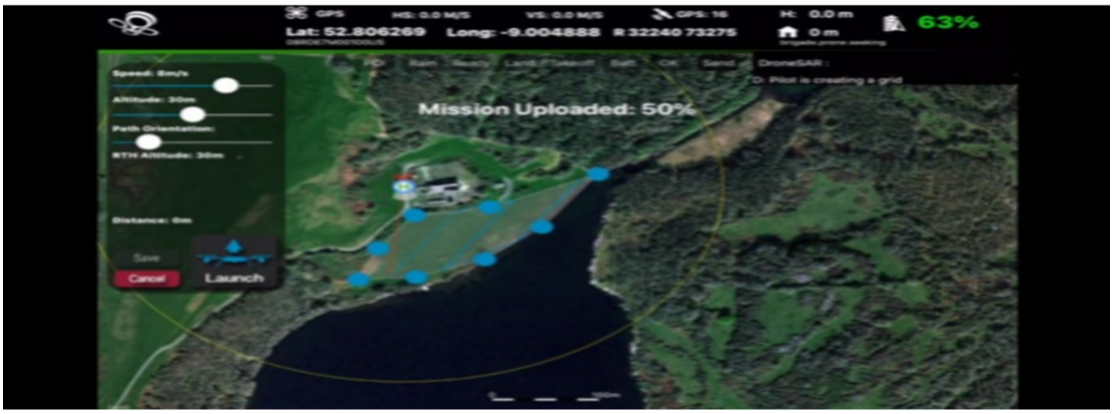
In this publication, the main advantage of the UAV unmanned vehicle is that it can reach much faster and inaccessible places that a human cannot directly approach to act. Thus, when the person is at the point indicated by the UAV, he now has a complete picture of the situation. After we have collected the image or video, the detection and notification of a possible emergency follows, that is, a sequence of assessing the situation. More specifically, objects, people, vehicles as well as anything else considered as a suspicious object are detected and provided by means of the YOLOv2 algorithm a better and reliable picture of the possible dangers so that the emergency warning system can be activated. This data is collected and processed after first being entered as input to a decision engine which automatically checks and evaluates the data to avoid human error and then with a faster decision determines the warning if we finally have an emergency picture. Here's an illustrated example that shows an emergency situation.

In this application “A Fast Object Detector Based on High-Order Gradients and Gaussian Mask Process Regression for UAV Images” (Reference 23), special emphasis is placed on the height of the UAV drone. The flight altitude of the UAV drone is about 2 kilometers from the target to detect a human figure or some object, and the detection is done by the shadows created by the image capture or the video transmitted by the UAV drone.

First, the algorithm used locates the targets (human figure, object) using Maximally Stable Extremal Regions (MSER) as a blob detection method in images. Then the spots of the detected targets are given as inputs to the filter algorithm for human or object detection. This is achieved, with various elements from the image or video capture by the UAV drone such as the angle of capture, the day/night situation, the time when the image is transmitted due to weather conditions. In this way we minimize the possibility of false targets, for example a person being detected as too large or too small for the situation in which the image was taken. In more detail, in order to successfully identify a person or object as a target, we must have only a person/object pair with its corresponding spot that matches. However, in order to have better results of successful targets in identifying the reconnaissance we also take into account the historical data if we have any.

It is worth emphasizing that this application is used to identify fires by tracking thermal cameras from the UAV drone that monitors various forest areas. In the case of a possible fire source, the MSER algorithm detects with its method the corresponding image recorded by the thermal camera of the UAV drone and then follows the color check to confirm if there is a possible fire source with an emphasis on whether the corresponding coloring falls.

UAV drone SAR is an online application "UAV drone SAR - Search & Rescue- https://www.dronesarpilot.com" (Source 24) created after several studies and research on the use of UAV drones for the deal with an emergency. It offers important information to local organizations and agencies that are limited in time and resources i.e. do not have UAV drones. The operation of the software is based on real emergencies that alert the agencies involved to deal with the situation. Here is a demonstration of the SAR drone mission execution as shown in the image below.

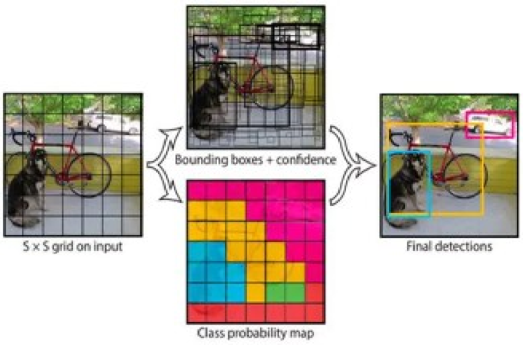


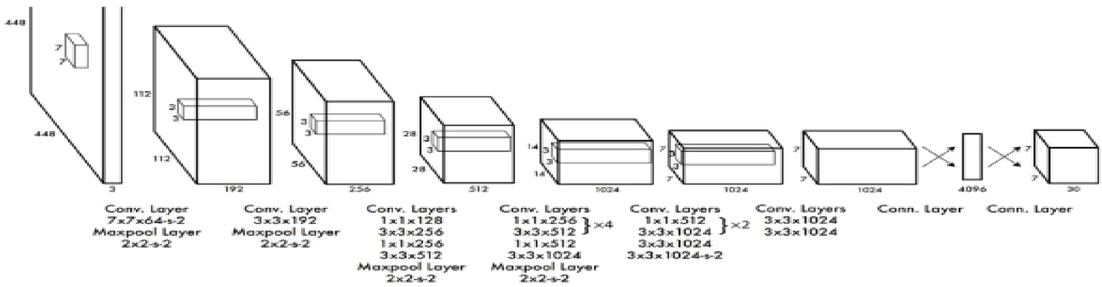
A series of actions are provided to send the information to electronic devices (computer, smartphones, tablets) as well as to someone's mobile device that has the SAR drone application. More specifically, you can choose the custom grid function, where you search for the area you want to check. You can also choose the routed mission "Waypoint Mission". In this defined mission the UAV drone SAR follows specific points selected on the map. Also, it is possible to know the longitude and latitude of the point where you located the emergency by selecting from the menu Lat/Long Mission. Multiple available information (eg weather conditions, accessible place) during the flight of the mission on the screen of the electronic device or mobile device of the user using the UAV drone SAR online application.

Finally, it is possible to broadcast live image or video capture from the point where the UAV drone SAR flight takes place, emphasizing the notification of its location.

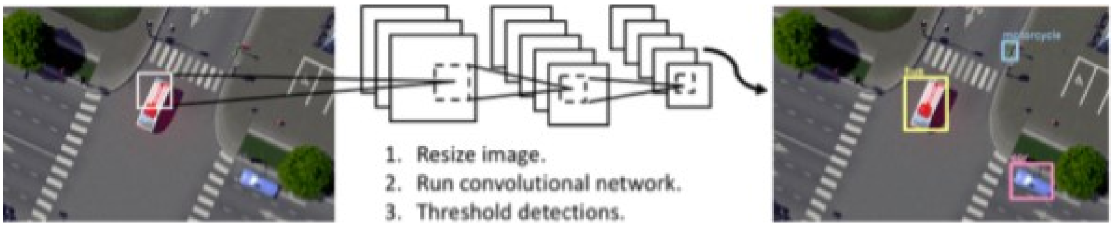
Methodology/Materials and Methods

The You Only Look Once (YOLO) recognition model is proposed to use a neural network (CNN) that directly processes the image or video and places boxes with the corresponding recognition in each case. Specifically, YOLO divides the image into small boxes and checks the probabilities for each class separately where other models use classifiers. It differs from the approach taken by other object detection algorithms and offers high accuracy of its results at high speed. It is one of the fastest recognition models due to the great variation that exists in the way the objects in the image or video are recognized. The model architecture of the YOLO algorithm which takes the image as input and then processes it with a simple deep convolutional neural network (CNN) to perform object detection is described below.



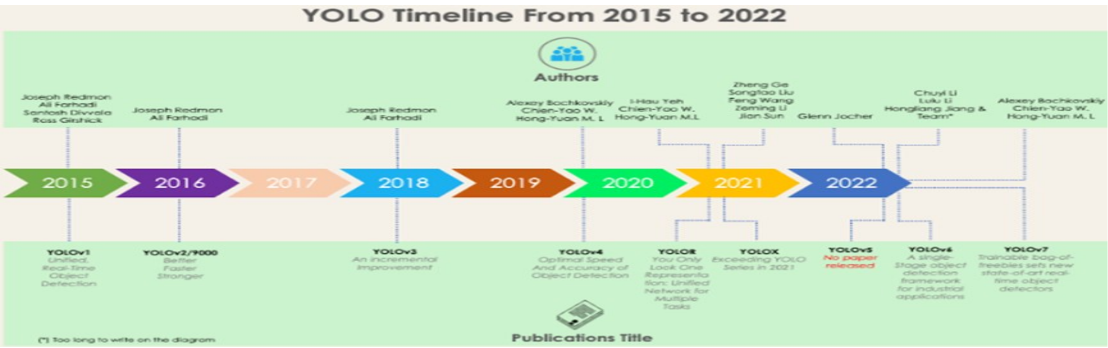


This fundamentally different approach to YOLO object detection has achieved cutting-edge results, with a great deal of variation in how recognition is done. In other networks, methods are used to locate objects with box-building algorithms that use model classifiers. YOLO's operation is quite simple and performs only one iteration for the same image or video while the other networks perform multiple iterations in the area of boxes for the same image. More specifically, first the image is resized and then the network used performs the predictions on the boxes and the class probabilities for them only one iteration in real time with a large difference compared to various other models. This process classifies the image recognition, which aims to predict the class of the image (an object, person, vehicle, etc.) from the image into one of the recognition classes as shown in the figure below.



A key method that the YOLO model uses is Non-Maximum Suppression (NMS), which is a processing technique used for object detection. NMS is used to more efficiently refine and eliminate multiple bounding boxes for the individual object in an image. To detect objects and display the bounding boxes around the image or video we perform detection processing (NMS) using cv2.dnn.NMSBoxes() method and cv2.rectangle() method of OpenCV library.

Therefore, YOLO can recognize objects in real time, such as objects, people, vehicles, etc. It is important for surveillance systems such as aerial navigation of a UAV drone that collects image or video data that then needs to detect objects with the using the YOLO model. As a result, the model is robust and reliable in real-time in recognizing certain things (objects, people, vehicles, etc.) in an image or video. Several new versions of the YOLO model have been released since its initial release in 2015. Here's its timeline showing that each version builds on and improves upon its predecessor.



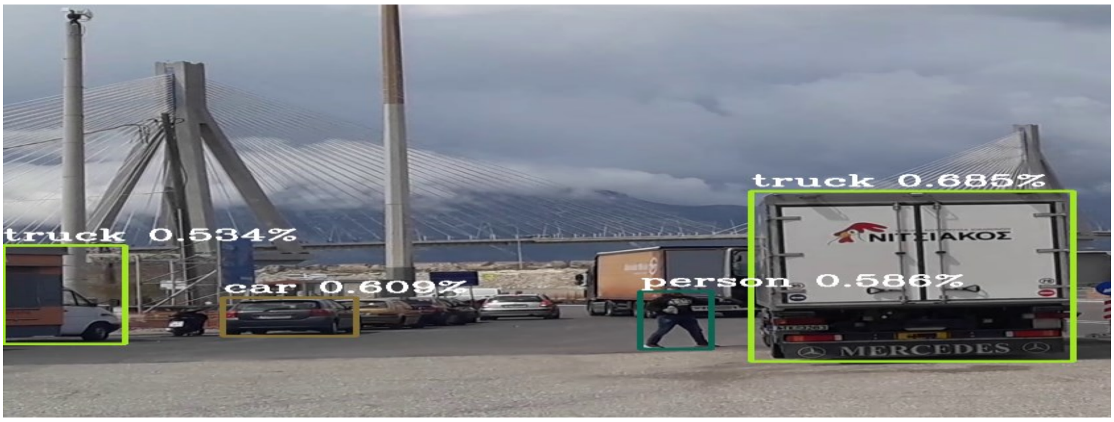
Additionally, the main advantage of the YOLO model is its fairly fast inference speed, since the network recursively recognizes the image and has a simple pipeline. It also processes the whole image at 45 fps in the simple version while the fast version at 150 fps during training. This implies that it thus implicitly encodes information about classes as well as their appearance. The same can be true for video, in real time with less than 25ms latency. Given the gradual evolution of the YOLO model, it is undoubtedly a leading model for object detection in both images and video streams using even deep learning (Deep Learning), computer vision (OpenCV) and Python programming language. Compared to various other models such as DPM, R-CNN and Fast R-CNN, which are also well-known object recognition models slower in speed and do not predict as accurately the background of the "backround" image by identifying several times misidentifications, since they do not understand the picture as a whole.

Experimental Study

The application code is programmed in Python, OpenCV, YOLO language and uses deep learning (Deep Learning) with convolutional neural network detection algorithms (R-CNN, Fast R-CNN, Faster R-CNN). The application should recognize people, objects and vehicles at the output of a video or image capture (Real Time). With this type of identification and detection, Object Detection is the computer vision technique (OpenCV) that allows us to recognize from each UAV drone and locate objects with the logic of technical intelligence (Artificial intelligence). Accurately identifying and identifying the video or image output is assigned a tag to the "interested" object.

The YOLO model detects where each object is and which label should be applied. In this way, object detection is subject to the analysis of Machine Learning-based approaches and Deep Learning-based approaches providing more information about the video or an image than traditional approaches to recognition. These approaches use to identify groups of pixels that may individually belong to an object. This then feeds a regression model with the help of a convolutional neural network (R-CNN, Fast R-CNN, Faster R-CNN) object detection algorithm that approximates the location of the object and gives its label at the same time.

The purpose of the application is to detect objects with an emphasis on identifying one or more "interesting" targets from data of a video or image capture (Real Time). The code for the application script from the UAV drone to track multiple real-world targets is achieved with “tracker object.py” a tracking object written in Python. It is a motion detection object class of people, objects and vehicles that tracks and records information related to the particular video or image. Its creation has box id and point id methods of each object already located. It updates the object detection dataset that is coco which categorizes the features it has in the video or image output. Following is a code snippet of the motion detection object class.



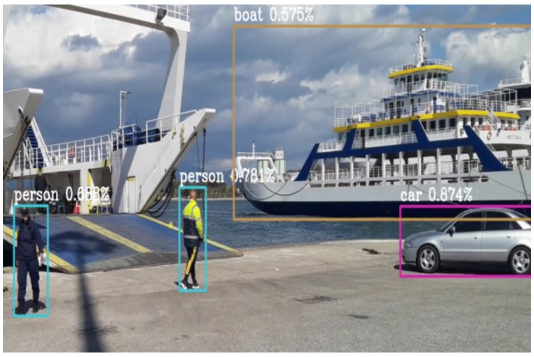
The main code provides all the necessary libraries and functions for the final implementation of our application. The model selected is YOLO with the Tracker class object required to draw the box rectangle around each object. Whether it is a ship or a face or any other object from the coco visual dataset it is drawn correctly as the convolutional neural networks detection algorithms are executed. First, the video recorded by the respective UAV drone is loaded which detects and recognizes each category of the object it detects. Its exact determination is made by the hundredth appearance of the name of the recognition of the snapshot of the image through the video using the computer vision technique (openCV). After the video is executed, the drawing of the box at the specific points is written in the python terminal the number of objects detected as well as their category and other information as shown in the table below.

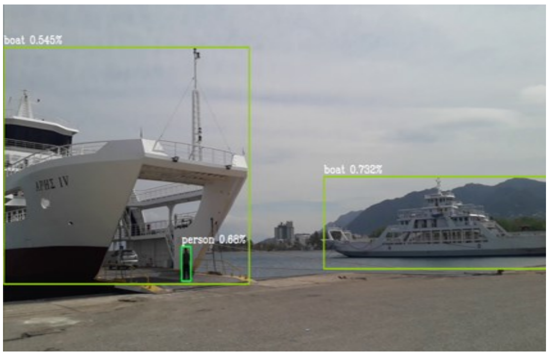
The extraction of the region of interest of the image from the video can be changed by the dimension values given each time to run to resize the video "frame" in the width and height fields to better optimize the object detection. In case we want to "freeze" the image, i.e. stop the execution, the command that is executed automatically by pressing the "q" button is the following line of code:

```
{ if cv2.waitKey(1) == ord("q") :
        break }
```

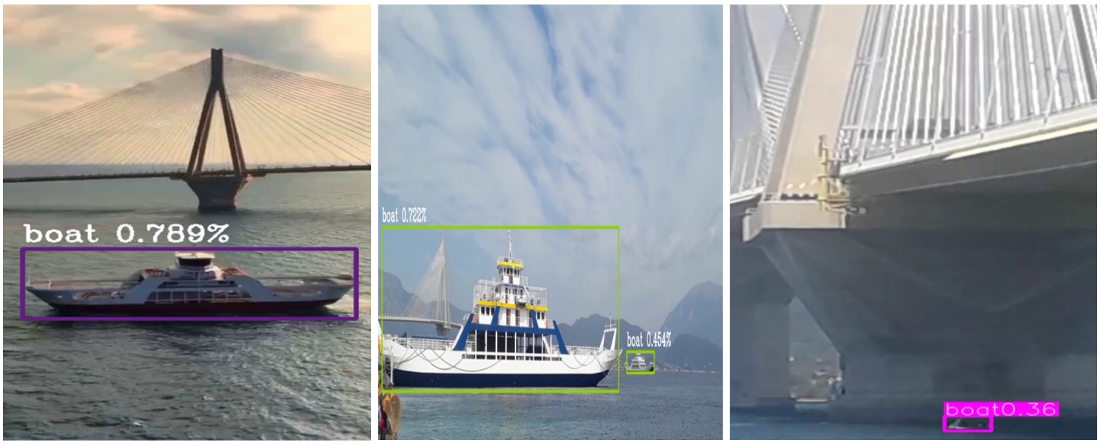
which momentarily ends the video playback and allows the user to better focus the image detection on that particular snapshot. Since we imported the necessary openCV libraries into python, read the sample video (rio.mp4), trained the YOLO model, used the coco visual dataset for the predefined detection objects, and as a result detected and recognized the interesting object accurately from objectTracker.py class (convolutional neural networks trained for object recognition).

In each case any video is loaded, the actual video stream from the UAV-drone camera to detect the presence and locate the position of multiple classes of objects from coco a visual dataset which is an important role for computer vision technique (OpenCV). Understanding the visual scenes in the video or image that includes object recognition and determining the object's characterization using the label indicates that the object recognition process has been efficiently and accurately focused on: (1) complete classification of the images that locates, (2) defined box border on each object, (3) segmentation of the pixel groups of each object, (4) segmentation of the "interested" object by highlighting its label. All the above information details for object detection, for example when running a specific video to search for images in real life scenes eg people, vehicles, ships, etc. See the screenshots of the following images taken from the video or image.

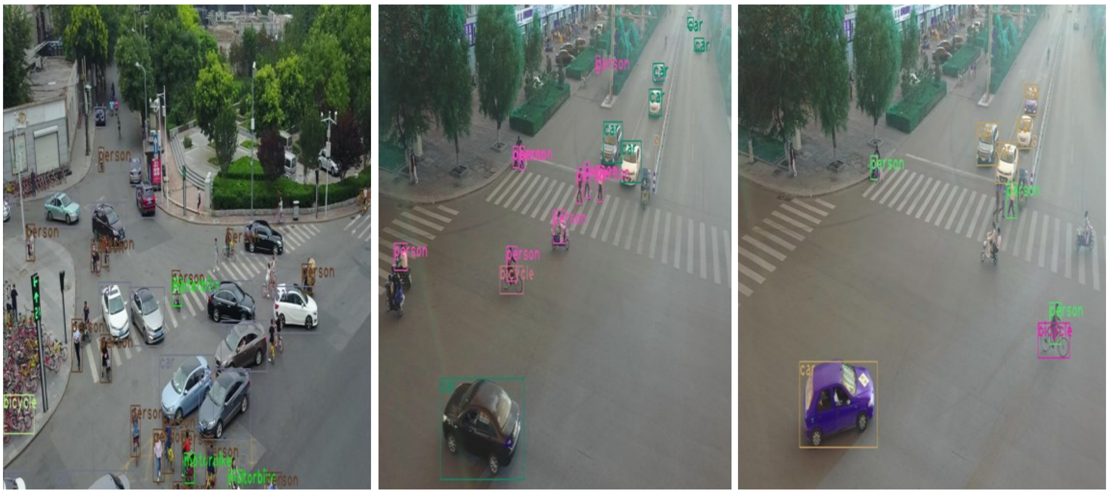




It is worth pointing out that the detection of objects in real time (Real Time) can be extended to the surveillance of the traffic of driven vehicles on ships but also within the jurisdiction of the port and in many other areas. Sample results that recognize certain things in an image or video are shown below as application hardware that generalizes more in detection and performs better in improving the detection model.



As mentioned above, computer vision object detection technology is already essential for many applications. We use it in other places too. As such, we can see snapshots of scenes from yet another **VisDrone** dataset collected by the AISKYEYE university team at China's Lab of Machine Learning and Data Mining. The dataset is practically implemented in yolov7.py for detecting objects in static images. Note that, the set of image data collected by drone shooting under various weather and lighting conditions. This highlights, how important and excellent it is to detect object targets under special conditions, providing a better use of the data. It aims to detect objects of predefined categories (eg vehicles, people, motorcycles, bicycles, etc.) from individual images taken by a drone. Examples of object detection in images as shown below.



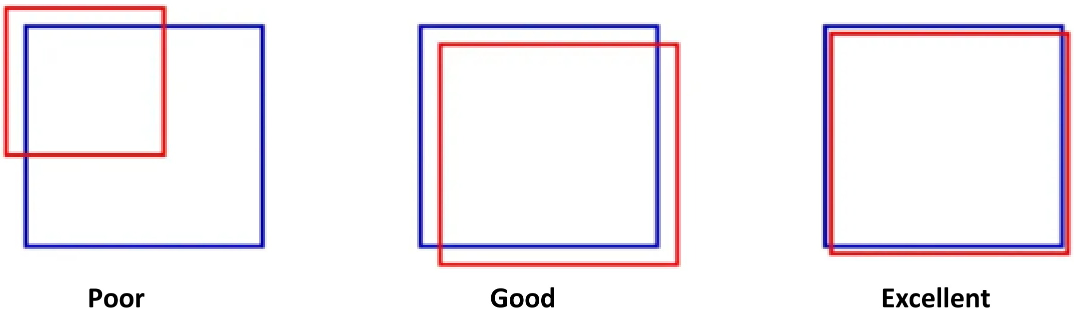
Intersection over Union (**IoU**) in object detection is an essential measure used to evaluate and evaluate the performance of the **YOLOv7** algorithm in object detection within an image. The ratio of the intersection of the predicted bounding box and the overlapping ground truth bounding box to the union of the two bounding boxes is calculated. Accordingly, a value of **1** indicates perfect overlap, while a value of **0** indicates no overlap. Then, if the corresponding IoU score is higher than a specified threshold for an object of the predicted bounding box it is considered as a "correct" detection. The two frames overlap or intersect each other as shown in the image below, we can calculate the point of intersection (**IoU**) which is the ratio of the overlap area between the two frames to the total area of the combined frames.

For example, the red grid cell predicts the "ship" object whose center is inside the purple grid cell. Also, each grid cell provides a fixed number of bounding boxes. For example, the red grid cell makes a bounding box prediction (purple box) to locate where the "ship" is. Additionally, the one-object rule limits how close the detected object can be. Let's describe in more detail what the output looks like. Each frame cell contains 5 elements: (x, y, w, h) and the frame confidence score . The confidence score reflects the prediction of how likely the box is to contain an object (objectivity) and how accurate the bounding box is. We normalize the bounding box width w and height h to the width and height of the image. x and y are offsets to the corresponding grid cell. Therefore, x, y, w, and h are all between 0 and 1. In other words, each cell will predict the confidence value for each bounding box. This is a probability that a grid box contains an object. But in case we have not detected an object in a grid cell, it is important that the confidence value is lower for that grid cell. In this way, we visualize all the possible predictions, we get a map of all the detectable objects that are in the image with a bunch of frames sorted by the confidence value of each frame. The bounding box contains:

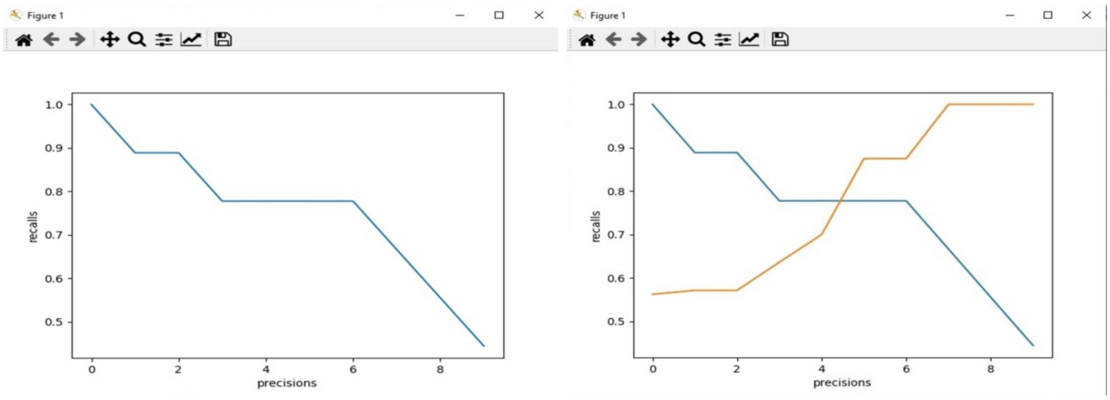
• [x01, y01] which refers to the upper left point of the bounding box.

• [x11, y11] refers to the lower right point of the bounding box.

Next, we proceed to intersection over union (**IoU**) which is a common evaluation metric used in object detection to measure the accuracy of predicted bounding boxes. That is, it compares the predicted bounding box to the ground truth bounding box and calculates the ratio of the section area to the joint area.



Since we measure the overlap between the predicted bounding box and the ground truth bounding box. In the case, a higher IoU value indicates that the predicted bounding box matches the ground truth bounding box better, thus providing a more accurate object detection. The **IoU** values range from **0** to **1**, with a perfect match having an **IoU** value of **1** and no match having an **IoU** value of **0**. As the image evaluation finishes, we will evaluate the **Yolov7** object detection model on the test dataset and finally compute the average **IoU** (**Intersection Above Union**) of all images and print it to the screen.



This means that there is an overlap of **93%** between the ground truth boxes and the predicted bounded boxes. By observing the boxes, we can visually see that it is excellent enough to conclude that the model has detected the ship object.

After calculating the intersection over union (**IoU**), we know whether a region has an object or not. The higher the percentage (**IoU**) the better the prediction of the object. Also, when the (**IoU**) is greater than the predicted limit stored in the thresholds list, it will generate values for the precision (**precision**) and recall (**recall**). Therefore, the frame is classified as **Positive** as it surrounds an object. While in a different case which is smaller it is classified as **Negative**. The next step is how to calculate the mean accuracy (mAP) for object detection.

To calculate the average **AP** accuracy for the class, we have the following parameters:

1. y_true = ["negative", "positive", "positive", "negative", "negative", "positive", "positive", "positive", "negative", "positive"]

2. pred_scores = [0.32, 0.9, 0.5, 0.1, 0.25, 0.9, 0.55, 0.3, 0.35, 0.85]

The stored **thresholds** list of limits (IoU) is initialized from 0.2 to 0.9 in 0.25 steps. Next, the code portion of the precision_recall() function table 12 which accepts the truth labels, prediction scores and thresholds. Returns the precision and recall values with a precision-recall curve plot. Based on this **precision-recall** curve plotted from the values the mean **AP** is **0.889**.

The recall precision curve facilitates the average precision (**AP**) to be set at a single value that represents the average of all precisions. According to the chart figure, the best average **AP** value is **0.889**. It is important to mention that the higher the value of the average accuracy, the more certain the object is classified as a **Positive** sample. As, and higher value of recall, indicates more positive samples in the object that were correctly classified as **Positive**.

Conclusions

In the context of the completion of the thesis, it is worth highlighting and highlighting a number of positive conclusions, which emerged from the surveillance and detection of the aerial flight of the UAV as well as the process of executing the practical software implemented for an honest capture of the result for recognition objects in marine areas. Beyond this, however, it is equally important to mention the personal benefit that results from the completion of a UAV that can be used in the field of shipping.

As it is known, UAV-drone mapping is now widespread in scientific fields that have the ability to act on a mapping, an analysis and digital image, the location at any time of a ship, observation control to avoid an incident and anything else they seek to carry out extensively until the whole process is achieved.

On the one hand, in relation to the way the situations are recognized for displaying the live image transmission from the UAV, it should be mentioned that it is an aerial vehicle that separates the physical presence and the inner commands are done automatically. In relation to the quantitative results we obtain through the UAV camera, it carries results of greater detail and analysis than traditional on-site autopsies. Being able to identify targets is more beneficial for exploiting and dealing with situations immediately without creating fear of dealing with them later. This software produces a live video stream by scanning a dataset of images, segmenting the popular objects identified with tags and available for public use.

On the other hand, modern solutions of UAVs - drones based on technical intelligence (AI) are still able to produce useful work for accurate results, in the fact that the COCO dataset used in the software is an important reference point for training, testing and improving models for faster scaling of the whole process. In addition, the COCO dataset is a complement to the processing of the data and to the segmentation of the snapshots imaged by the camera of the smart UAVs – drones.

However, smart UAVs – drones can serve "key" point detection situations that benefit the manager who monitors the live image and can create a response framework until he goes to the specific point where an incident is taking place. All operational situations require coordination between the various situations you will face, it is equally useful to know and operate more methodically to complete a successful situation where it was necessary to demonstrate the capabilities of UAVs – drones with the contribution of the software that includes a COCO data set , a huge range of objects, things, materials that we encounter in our daily life. Is a reference standard for the methodology of analysis and assessment of detection in marine areas. I hope that this effort will find fellow travelers and continuers who will be possessed by the same enthusiasm as me.

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