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A Study of Detection and Tracking of Artificial Intelligence in UAVS using Machine-Learning Approach

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Abstract**—** This article explores the development and testing of a system for detecting multi-rotor unmanned aerial vehicles (UAVs), a critical need in sectors focused on safeguarding sensitive structures and preserving privacy. Initially employing computer vision techniques, specifically the Oriented FAST and Rotated BRIEF (ORB) feature detector, the study found its real-world applicability limited, prompting a shift towards a machine-learning based detection method. To enhance the model's accuracy, the Common Objects in Context dataset was supplemented with 1000 UAV samples from the Safe Shore dataset. The system's efficacy was evaluated through four rigorous experiments, encompassing scenarios with a single UAV and multiple drones captured in both static images and video footage against sky backdrops. Achieving a notable detection success rate of 97.3% under optimal conditions, this study demonstrates the potential of integrating advanced machine learning techniques with enriched datasets for reliable UAV detection in diverse operational environments.

Keywords- UAV; detection; machine learning; Tensor Flow; ORB.

I. INTRODUCTION

Algorithms for object identification and classification rely on the fact that the items under consideration share certain features. So characteristics aren't only what they seem like; their activity or movement also defines them. UAV recognition is concerned with both things that may be found inside the sensing region and with UAVs themselves. A UAV's form is one of its most distinguishing visual characteristics. From the tricopter to the octocopter, every kind of unmanned aerial vehicle (UAV) looks the same. tricopters are triangular in form, quadcopters are square, and so forth. Additionally, each UAV is made up of a unique set of hard components that give it its own distinct aesthetic appearance. Depending on the number of propellers, this design may have anywhere from three to eight arms with storage space in the centre for the control board. The propeller is hung from the engine, which completes each arm. Almost every UAV may utilise this basic appearance design since it is universal. UAVs in the nano and micro size categories, however, may have their propeller and motors placed directly on the UAV's centre panel. A major benefit of these machines is their longer battery life, which allows them to stay in the air for longer periods of time while also flying greater altitudes. Multi-rotor and fixed-wing drones can both take off and land from the ground, but most can only remain in the air for as long as they're moving. Another kind of drone exists that is smaller, lighter, and has a higher top speed than multirotor versions. In the drone industry, they are referred as as fixed-wing drones [3]. This is because of their characteristics, which make them popular in fields including environment and area mapping (with the potential for three-dimensional data production [4]), meteorology, and quality control inspections (an interesting example is the inspection of electrical wiring described in [5]). According to [1,] fixed-winged UAVs are well-suited for the aforementioned tasks due to their low cost of ownership, low operating costs, and short flight duration. Their operational range and flying safety are also major advantages, according to [2]. One benefit of multi-rotor models is that they allow for more precise environmental mapping, which is useful in civilian

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applications. Another advantage is that they are easier to operate. Because of the increasing popularity of these devices, as mentioned in [6,] more study and regulation will be needed to guarantee their safe use in the future while still allowing for normal airspace, traffic, and management. Additionally, UAVs may be identified by the presence (or lack) of certain parts. For example, certain unmanned aerial vehicles (UAVs) include a ring that surrounds the whole machine's perimeter. Other UAV kinds, on the other hand, have components that are fully exposed. An extra covering ring may or may not be used by certain kinds of UAVs, depending on where the machine propellers are placed. A camera is standard equipment on the vast majority of unmanned aerial vehicles (UAVs). The camera may be tucked away within the UAV's fuselage, making it almost invisible. However, better-quality cameras on UAVs place the camera towards the bottom of the UAV, making it a more conspicuous component of the overall design. Additional gadgets distinguish a number of UAV kinds. For example, robotic arms and other equipment are often seen on large-scale unmanned aerial vehicles (UAVs). It's important to note that the suggested detection and identification method doesn't take big extra devices like these into account.

Main objective is to develop and implement an automated detection method that can be compared with the typical human observer gazing into space. This study is primarily focused on automated detection. Using the suggested method, multi-rotor drones will be identified by the way they look. We concentrate on these drones because of the wide range of civic uses to which they may be put. UAVs that have a light device on their lower bodies may be easier to notice in low-light situations because of the gadget's proximity to the ground. The manner in which a UAV moves is another distinguishing characteristic. Using the movement, an unmanned aerial vehicle (UAV) is moved from a stable location to another, where it may be stabilised once again. The unpredictability of the UAV movement as a whole is a problem. There are no sliding or wing-waving motions made by the UAV, like a bird might. Our study included a basic examination of UAV movement patterns, and the findings show that these devices move in predictable ways. Although the UAV's movement is mostly linear, it is capable of making quick changes in direction, speed, or altitude.. The unmanned aerial vehicle (UAV) has the ability to maintain its location and float in midair. These motions are a world apart from what you'd find in a bird. A number of cases of unmanned aerial vehicle (UAV) misuse for surveillance purposes or terrorist strikes have been documented. UAVs have also been used to smuggle contraband into prisons in the past. These are only a few of the possible misuses of these devices that necessitate identifying and tracking unmanned aerial vehicles (UAVs) in a region where assaults like these might occur. Because of the capabilities and flexibility of these devices' uses, there are many ways in which they might be abused. These aircraft have the ability to fly very close to the ground while simultaneously being able to soar very high. It is possible for them to hide behind a variety of things and fly in varied lighting situations while using extra gadgets to go around various barriers. However, in severe weather circumstances, such as heavy wind, rain, snow, pollution, or hail, we believe these devices will falter. In our study, we anticipate a substantially limited capacity to manoeuvre or make use of extra equipment, but we do not rule out the potential of utilising machines that are suited to such circumstances.

Existing Methods for Detection and Identification of Objects in an Image

1. Background Subtraction

The background subtraction technique is one of the simplest ways to find items in a picture because of how simple it is to use. The background model must be properly identified, as stated in [10]. Once this phase is complete, the background model is compared to the current picture and the previously known background elements are removed from the resultant image. When you don't remove anything, there's a good chance that new things may appear in the forefront. Typically, the backdrop refers to everything in the picture that is either stationary or occasionally moving. It's possible that the whole scene has elements that change over time, such as moving tree leaves and then-static ones. A module that subtracts a backdrop to differentiate between static and dynamic objects is a frequent part of systems whose goal is to monitor things using a static camera. Maintaining the backdrop model is a significant and time-consuming component of the background removal process. [11] states that certain conditions make it difficult to read or detect the background, such as uneven and variable illumination, changing spectral characteristics of the illumination and, as a result, different colours of the object, overlapping objects, different camera angles, and variations within a single category of objects. [12] presents a comprehensive comparison of the various background subtraction methods. This comparison was done to see which method was more effective in dealing with the aforementioned issues.

2. Contour Searching

Contours in image processing are used to create a curve that encompasses the picture's contents. The success of this object-bounding approach relies on picture preprocessing techniques like image smoothing and morphological procedures being used before the final image is generated. In order to use contour searching, the picture must be divided into "positive" and "negative" areas [10], whose borders may be regarded as objects with limited space]. This method's proper parameter setup ensures that picture contours are correctly detected. The word "contour" refers to a collection of dots on a picture that form a curve. Records contain information about the next point on these curves by representing them as sequences. The contour search tool may create a "contour tree" because of its structure. As a result, it's possible to tell which contours are kid contours and which are root contours [10,13]. Most of the time, just the root contour of an item has to be delimited when it is detected in an image.

Figure 1 depicts the segmented item on the left and the contoured object on the right, respectively. In addition to the root contour, there are many additional coloured contours representing various things inside the root. Since recorded objects are never homogenous, this phenomena may also arise following morphological procedures and picture smoothing. Since recorded objects are never homogenous, this phenomena may also arise following morphological procedures and picture smoothing.

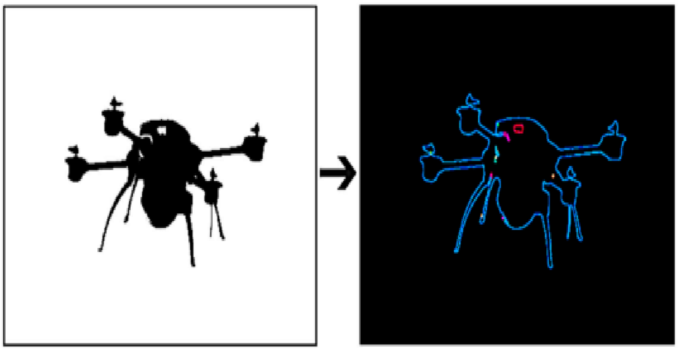

Figure 1. Contour searching applied to the edited image with a drone

3. Selective Searching

As reported in [14], this algorithm is based on three main assumptions:

1. Capturing all possible scales in the image—using a hierarchical algorithm, selective searching attempts to take into account all possible scales of the objects;
2. Diversification—since objects in the analyzed area are subject to different changes such as illumination, shadows, and other, selective searching does not use a uniform strategy for a subregion search;
3. Calculation speed—since the step of subregion searching is only a preparation for the object recognition itself, this algorithm is designed to not cause any decrease of calculation speed.

An example of subregion searching in a static image using a selective searching algorithm is shown in Figure 2.

Figure 2. Selective searching in the image with drones

4. Drone Detection Using Computer Vision Methods

For our detection procedure to be effective, we must be able to recognise and identify moving objects in an image, correctly match objects from the previous frame to the current location of the objects in the image, and draw the path of an object in a scene. These requirements and objectives must be met. As a result of this, a computer vision-based detection method was developed, as shown in Figure 3.

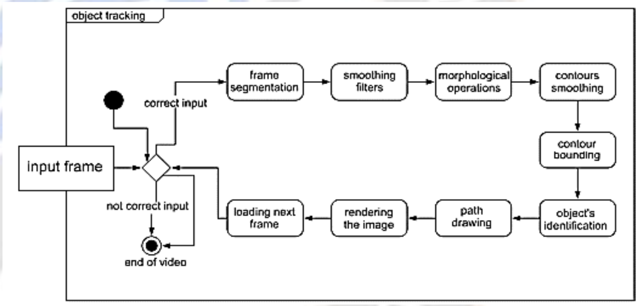

Figure 3. The basic scheme of the proposed detection procedure

The background segmentation is the initial stage (Figure 4). Because of its flexibility to changing lighting conditions during the day, the MoG (Mixture of Gaussians) technique was selected as one of the evaluated methods (not sudden changes as switching on the light in a room) a little movement of background items that don't reflect anything important in the picture, and which might be obscured by a larger one. During the image's drone detection, anticipate to see all of these situations.

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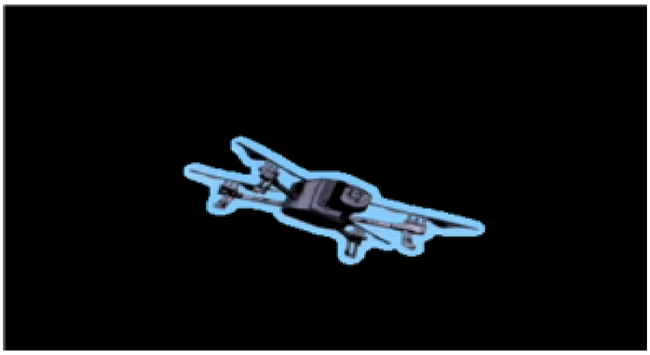

Figure 4. Segmentation of objects using the MoG (Mixture of Gaussians) method (background has black color).

Once the filters have been applied, the picture will be finished. It's essential to level down any peaks and valleys. The great noise reduction effectiveness of the Gaussian filter [21] was chosen above the other smoothing techniques, thus it was selected as the final smoothing method.

5. Detection and Identification of a Drone Using a Machine-Learning Approach

In order to find a neural network appropriate for the identification of multi-rotor UAV machines, machine-learning techniques will be used. We've selected the Tensor Flow machine learning platform since it's readily accessible and up-to-date. It was then up to us to over train the network with the proper network parameters and evaluate its success rate in categorising objects in the sky into the many categories we were considering utilising it for. The following are the stages that make up our solution and approach:

- Preparing data for training;
- Preparing data for evaluation;
- Selection of detection model;
- Creating other necessary files for training;
- Training;
- Export of the trained model to a frozen graph format;
- Creating an application to test the detector.

5.1. Preparing Data for Training and Evaluation

Enough data must be collected to enable effective neural network training. Photograph the subject in a variety of lighting, spatial, and other situations. All of the specified drone kinds must be shown in various circumstances, rotations, and settings, as well. To train the network and identify the item of interest, there needs be enough data gathered. Annotations indicating the precise position of the item in the scene are required in addition to the collected data.

5.2. Selection of Detection Model

In order to save time and processing resources, detection models that were trained on the "Common Objects in Context dataset" were employed after all other options had been explored and shown to be ineffective. In all, there are over 200,000 annotated pictures in this collection of over 200,000 different classes (such as cat and dog) that may be utilised for training. The drone, on the other hand, is not one of them. Conversely, since all the training parameters are tailored to particular detection, creating our own detection model would be more reliable than utilising a pre-trained one.

5.3. Creating Other Necessary Files for Training

A significant quantity of data is required for the model's training to be effective. As a result, the pictures captured by the drones came from publicly accessible online resources. They numbered perhaps about 100 people. Another 1000 samples were acquired after speaking with the Safe Shore project's creators, who were working on a project sponsored by the European Commission to identify tiny objects flying at low altitudes. Video sequences of a flying drone were used to generate other samples.

5.4. Training

The library's creators have made a training script available in their official Github repository. In Tensor Flow, just the CPU support of 3,5 GHz was needed, thus each training step took around 4.5 seconds on average. Tensor Flow with NVIDIA GeForce GTX1050 Ti GPU support took an average of 0.33 s each training step, so that's what we're going with. As a result, the difference in training timeframes is heavily influenced by the detector's training method.

6. Conclusion

The Tensor Flow library was used to create a dependable multi-rotor UAV detection method. The "Common Objects in Context dataset" was utilised for this, and the Safe Shore dataset was supplemented with 1000 additional samples of unmanned aerial vehicles (UAVs). In ideal circumstances, a detection success rate of 97.3% might be obtained. It's safe to say that the suggested detection concept worked well in the real-world testing scenarios detailed here. The trained detection model performed well in all of the scenarios in which it was put to the test. Only in the presence of objects from a different class that had comparable characteristics did we run into a difficulty. According to the detection model's statistical assessment, only 61.3% of the samples were detected. Furthermore, no sign of the bird should be seen. Because of this, a different kind of detection model was used. Drones and birds may be distinguished using this approach. According to the results of the tests, the detection was significantly more effective when the detector was trained on multiple items. As a result of this discovery, we've come to the conclusion that items with identical characteristics are the greatest obstacle to drone identification. Objects like a bird, aircraft, parachute, or paragliding wing may be compared to the drone. Because there are fewer of these items, a detection model may be trained on a larger data set. Such a detector may be even more effective than the one that was developed via the use of two separate courses of training. However, for most basic security applications, a detection rate of 97.3% of the detector trained in two classes is adequate. It's possible to compare success and system dependability to what you'd see in the real world. All specified data and circumstances were put to the test, and the results show that our method works well for detecting multi-rotor drones under perfect flying conditions.

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