Evaluation of the required optical resolution for deep learning-based long-range UAV detection

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1. ABSTRACT

This paper evaluates the required resolution of a telescope system experimentally to enable a reliable deep learning-based long-range UAV detection. FRCNN, a state-of-the-art deep learning object detector is fine-tuned for UAV detection with a custom dataset. A test dataset has been created of a small UAV in front of a clear and complex background at distances ranging from 500 m up to 2500 m using a telescope with a focal length of 1325 mm and an aperture of 102 mm. At each distance the resolution is measured with a modified version of the US Air Force resolution chart. The results show that a small UAV is detected with a mAP(0.5) of above 90 % in front of a complex background up to a distance of 1167 m given a minimum resolution of 9.3 mm or 8 µrad and up to 2222 m in front of a clear background given a minimum resolution of 38 mm or 17.1 µrad.

Keywords: Deep learning, resolution, telescope, UAV detection

2. INTRODUCTION

The trend to cost-effective small Unmanned Aerial Vehicles (UAVs) has resulted in a growing number of threatening and dangerous scenarios, posing heightened risks to critical infrastructure, including airports and power plants. On multiple occasions air traffic in major European cities such as Dublin,[1] Berlin,[2] and Nice[3] had to be temporarily halted or experienced significant delays due to the presence or even collisions with UAVs, underscoring the disruptive impact this technology can have on aviation operations. Small drones also have been illicitly utilized for illegal transportation of narcotics across national boundaries[4] and engaging in espionage, with a particular focus on the surveillance of critical infrastructure such as power plants and other strategically significant installations.[5] Therefore, UAV detection systems are crucial to identify the incoming threat and to prepare counter measures.

As a consequence, a lot of research and development is focusing on UAV detection. A typical UAV detection system combines different sensors including LiDAR,[6] RADAR,[7] acoustic sensors,[8] RF (radio frequency) based systems[9] and optical systems.[10] Optical detection relies on computer vision to detect and track an object. Detection is accomplished through the utilization of deep learning algorithms, which have consistently demonstrated their effectiveness over the years. State-of-the-art algorithms like SSD,[11] FRCNN,[12] and FCOS[13] have proven to be robust solutions for detection tasks and numerous studies utilize these algorithms for UAV detection.[14,15]

To obtain a high quality image, a suitable camera system has to be selected to capture the UAV with sufficient pixels covering the object for a reliable detection by a neural network.[10] Typically, cameras are used with a narrow field of view mounted on pan-tilt devices to enable surveillance of a large area.[16] Long focal lengths and large apertures, for example offered by telescopes, further increase the detection distance.[10] At long distances, the atmosphere has a greater influence on the image quality and limits the achievable optical resolution. In order to design and select suitable optical components to enable long distance UAV detection, an adequate experimental analysis of the necessary resolution is required. The optical resolution can be measured for example by using resolution test targets with the Contrast Transfer Function (CTF), or the application of the Modulation Transfer Function (MTF) through slit illumination.[17] Determining the achievable resolution of an optical detection system and correlating it with the detection probability of a neural network for UAV detection is a crucial

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aspect to determine the limits of the system at hand.
The contribution of this paper is the experimental evaluation of the required resolution for a telescope-based long distance UAV detection system to achieve reliable deep learning-based UAV detection.

3. METHODOLOGY

3.1 Telescope setup

The investigated system consists of a Celestron NexStar telescope (Celestron, USA) with a focal length of 1325 mm and an aperture of 102 mm. The camera used for image acquisition is an ASI 385 MC-Cool (ZWO Company, Suzhou, China) camera with a sensor diagonal of 8.37 mm and a quadratic pixel size of 3.75 µm. Fig. 1 shows the telescope system and camera on a tripod during field tests.

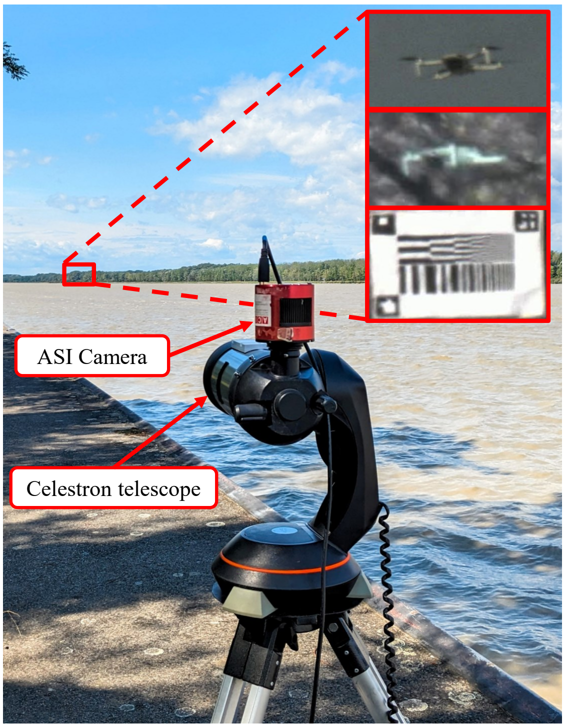

Figure 1: Schematic overview of the utilized measurement setup. In the distance the UAV and the resolution chart is illustrated.

3.2 Automated resolution measurement

An auxiliary software program is developed to automatically and consistently determine the optical resolution of the individual frames. A custom resolution chart, which enables automatic evaluation, consisting of black and white bars in different scales as seen in Fig. 2a, is created. The pattern is based on the 1951 United States Air Force (USAF) resolution chart.
The custom pattern consists of the mentioned bars, which are scaled down to a smaller size. The bars are plotted horizontally and vertically to determine the horizontal and vertical resolution of the optical system simultaneously. In order to automatically extract the achieved resolution, in addition to the horizontal and vertical bars, three ArUco markers[18] are added to the paper print as visible in the corners of Fig. 2a. Exploiting the rotation-invariant detection capabilities of ArUco markers, the corners of the resolution chart are automatically detected

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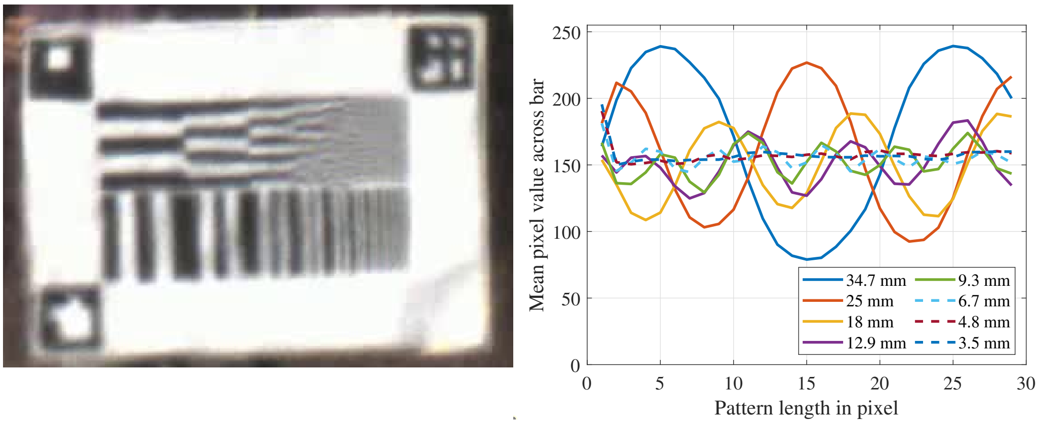
and possible rotational errors are corrected. This alignment enables the individually scaled sub-patterns to be separated by a precise image crop. Moreover, the paper format and the scaling factor of the black and white bars is stored as an ID within the AruCo markers to enable automatic determination of the width of each bar. If the ArUco marker detection fails, the alignment and the selection of the region to be cropped can also be done manually. Once the sub-patterns are extracted, the mean pixel value along the length of the pattern bar is calculated. Plotting the mean value over the alternating black and white bars, will create a sine-like function as seen in Fig. 2b.



(a) Example image of resolution chart.

(b) Extracted pixel values.

Figure 2: a) The custom resolution chart including three AruCo markers, which facilitate a simple detection and orientation adjustment for extracting the individual sub-patterns. The resolution chart imaged through an optical device under test. b) The extracted pixel values for each horizontal sub-pattern. The dashed lines are not discernable according to the threshold marking the lowest achievable resolution at 9.3 mm for this example.

The optical resolution of a frame is ascertainable by the bar width of the smallest distinguishable bars. To determine a threshold for distinguish-ability, 100 images of varying resolutions are inspected subjectively to discern, which pixel value difference between black and white bars is still distinguishable to a human observer. In addition to the described procedure, a mean value for the resolution is calculated over an entire video consisting of multiple images, to consider the fluctuating influence of the atmosphere within the measurement.

3.3 Deep Learning-based object detection

To find a correlation between the optical resolution and the detectability of a UAV, the deep learning object detector FRCNN[12] is trained. For the training process approximately 14000 UAV images are used,[19] whereas this dataset is split into 91 % training and 9 % validation data. FRCNN is initialized using the weights pre-trained on the COCO dataset[20] and then fine-tuned on the custom UAV dataset using an RTX 3080 GPU (Nvidia Corporation, Santa Clara, California, USA) with 10 GB of GPU RAM for 30 epochs. The learning rate is set to 0.0015, with a weight decay of 0.0006 and a momentum of 0.8. For a stepwise reduction of the learning rate, it is multiplied by a factor of 0.1 after epoch 22 and 25. During the training process, the models are evaluated using the validation dataset and the best model according to the mean average precision (mAP) at a threshold of 0.5 is selected and used for the final experiments in Section 4. Fig. 3 shows the overview of the loss and the validation score during the training process. The best model is obtained at epoch 25 and is extracted to be used for inference.

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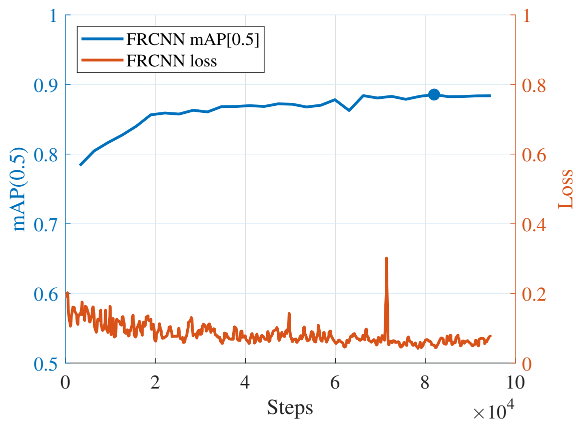

Figure 3: Overview of the training process showing the loss and the mAP(0.5) when applying the models onto the validation dataset. The blue circle marks the best performing model selected for inference.

4. EXPERIMENTS AND RESULTS

Figure 4: Example collection of images at various distances of the resolution chart and the DJI Mini 2 in front of a complex and a clear background. Note that the images are cropped around the relevant object.

For the experimental evaluation field tests are conducted using the presented optical system, the custom made resolution chart and a DJI Mini 2, which has a width of 289 mm. In order to experimentally validate the necessary optical resolution to detect UAVs at a certain distance, three measurements are performed per distance. A video is captured of the resolution chart in a distance x. At the same distance x, two more videos are captured of the DJI Mini 2 flying in front of a clear and complex background. In Fig. 4 example images are shown at various distances, ranging from approximately 500 m up to around 2500 m.

The results of the resolution chart measurements are evaluated according to the automated method described in Section 3.2. Within each video, the resolution chart is automatically detected via the ArUco markers or by manually selecting its corners. For longer distances, the ArUco markers are omitted to enable printing larger black and white bars. For these resolution charts, the region to be cropped is selected manually. The video

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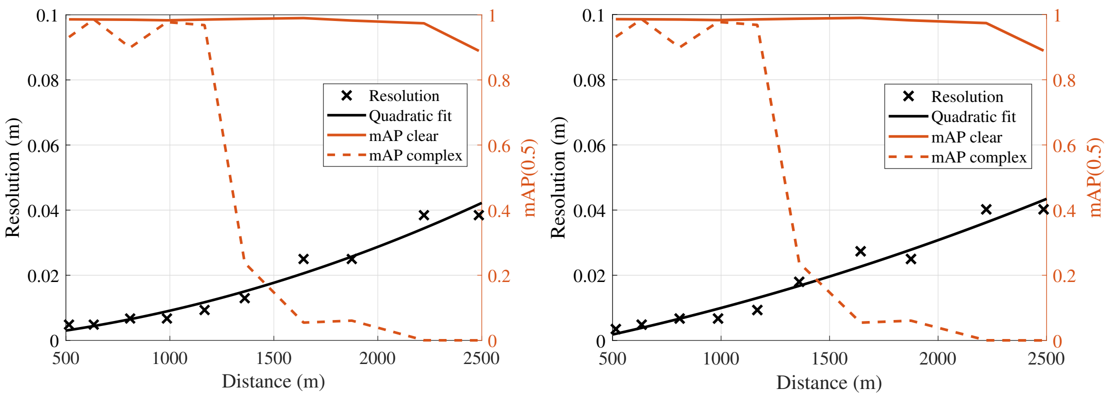
images are cropped to separate each sub-pattern of the resolution chart for evaluation. Evaluating a single image across all sub-pattern produces results as depicted in Fig. 2b. To consider the effect of the atmosphere onto the measurement, the mean of the obtained resolution is calculated over each video sequence, which last about 10 s at a camera frame rate of 60 fps.
To evaluate the results obtained by the deep learning algorithm, for each distance and background a 10 s video of the UAV is recorded at 60 fps. Every 6th image is extracted from these videos, which is about 100 images per background and distance, totalling to approximately 2000 images over all scenarios. These are manually labeled to obtain the ground truth for the subsequent evaluation. As an evaluation metric the mAP at a threshold of 0.5 is used.



(a) Horizontal resolution in meter.

(b) Vertical resolution in meter.

Figure 5: The resolution measured with the USAF resolution chart is shown over a distance from 500 m to 2500 m together with a quadratic fit of the data. Additionally, the mAP in front of a clear and complex background using a fine-tuned FRCNN object detector is depicted.

Fig. 5 shows the minimally distinguishable bar width in meter, which translates to the achievable resolution, and the mAP(0.5) over various distances. The results demonstrate that for a small UAV in front of a complex background, a minimal resolution of 9.3 mm or 8 µrad is necessary to enable UAV detection with a mAP(0.5) of above 90 % from a distance of 1167 m. For the case of a clear background the mAP starts to drop below 90 % at distances above 2222 m, where the measured resolution is 38 mm or 17.1 µrad. Presenting the results in terms of necessary number of black and white bars covering the size of the object to be detected, in front of a clear background it has to have at least the size of 7.5 times the achievable resolution bar width and for a complex background this factor increases to 31. It is expected that it is easier to discern objects in front of a clear background, as a higher contrast towards the constant and unchanging background allows the deep learning algorithm to detect the object better. In Fig. 4, the images of the UAV in distances above 1360 m illustrate the difficulty of detecting the UAV at low resolution in front of a complex background.
The presented measurements allow determination of system requirements of an optical system, when trying to detect UAVs of a certain size reliably. These numbers can be used to determine the size of the object, which can be reliably detected with a certain optical setup or also the required aperture when selecting an appropriate lens for a camera.
Summarizing the results, to achieve a mAP(0.5) of more than 90 % a minimal resolution of 8 µrad for complex and 17.1 µrad for clear background is necessary to detect UAVs of 289 mm in diameter reliably.

5. CONCLUSION

An experimental evaluation has been performed to correlate the optical resolution to the detection accuracy of a deep learning-based algorithm for the task of UAV detection. The results show, that for a detection of a UAV with a diameter of 289 mm with a mAP(0.5) of above 90 % using deep learning object detection, a minimum

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resolution of 8 µrad for a complex and 17.1 µrad in front of a clear background is necessary. The presented results can be used as a basis to estimate the requirements for an optical system to detect objects of a given size in a certain distance.

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