HIT-UA V: A High-altitude Infrared Thermal Dataset for Unmanned Aerial Vehicles

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Abstract—This paper presents a High-altitude infrared thermal dataset, HIT-UA V, for object detection applications on Unmanned Aerial Vehicles (UAVs). HIT-UA V contains 2898 infrared thermal images extracted from 43470 frames. These images are collected by UAV from schools, parking lots, roads, playgrounds, etc. HIT-UA V provides different flight data for each place, including flight altitude (from 60 to 130 meters), camera perspective (from 30 to 90 degrees), date, and daylight intensity. For each image, the HIT-UA V manual annotates object instances with two types of the bounding box (oriented and standard) to address the challenge that object instances have a significant overlap in aerial images. To the best of our knowledge, HIT-UA V is the first publicly available high-altitude infrared thermal UAV dataset for persons and vehicles detection. Moreover, we trained and evaluated the benchmark detection algorithms (YOLOv4 and YOLOv4-tiny) on HIT-UA V. Compared to the visual light dataset, the detection algorithms have excellent performance on HIT-UA V because the infrared thermal images do not contain a significant quantity of irrelevant information with detection objects. This indicates that infrared thermal datasets can significantly promote the development of object detection applications. We hope HIT-UA V contributes to UAV applications such as traffic surveillance and city monitoring at night. The dataset is available at https://github.com/suojiashun/HIT-UA V-Infrared-Thermal-Dataset.

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are widely used for various domains such as forest inventory [25], mapping applications [21], traffic monitoring [10], humanitarian relief [4], and so on. With the development of deep learning [18] and edge computing [23], UAVs can load artificial intelligence (AI) algorithms as edge computing devices, increasing the value in the above applications.

Motivated by the rapid development of object detection applications, many general datasets have been proposed to support algorithm training and evaluation. Meanwhile, are introduced for object detection datasets on UAVs.

However, although many datasets have been introduced for AI tasks on UAVs, there are many challenges in this field:

- Application range limitation. Most of the existing UAV datasets are collected by the visible light camera. The detection algorithms trained on these datasets cannot perform well at night because the light is so dark and the flight altitude is so high that the camera cannot capture the objects. This issue makes UAVs cannot be applied to many vital tasks such as traffic flow monitoring during the night.
- Insufficient information. Most UAV datasets do not contain some flight data such as flight altitude or camera perspective, etc., making researchers unable to explore many issues such as the impact of camera perspective and flight altitude on detection accuracy.
- Practicality. Many UAV datasets are collected in a small range of aspects such as low-altitude, a specific object, or a single scene. The high flight altitude can significantly promote the detection range of UAVs and has the advantage of accessibility in the city with tall buildings. The low-altitude UAV datasets will limit the range of applications for UAVs. In many object detection tasks, the UAVs are required to detect many different objects. For example, traffic monitoring needs to detect persons, cars, bicycles, etc. The datasets with the specific object cannot satisfy these tasks.
UAVs may be required to work in many scenes such as school, road, etc. The datasets with a single scene cannot train algorithms to satisfy the detection requirements of these scenes.

This paper presents the HIT-UAV dataset to address these challenges and promotes the applications of UAVs in dark environments, such as traffic surveillance and city monitoring at night. Its images are collected by the infrared thermal camera to expand the application range of UAVs at night. The HIT-UAV dataset recorded the information of the flight altitude, camera perspective, image date, etc., to help researchers research different issues such as the impact of UAV flight altitude or camera perspectives on the precision of object detection. The HIT-UAV dataset covers a wide range of aspects, including higher altitude (from 60 to 130 meters), different camera perspectives (from 30 to 90 degrees), various scenes (schools, parking lots, roads, playgrounds, etc.), different common objects (person, car, bicycle, vehicle), etc. to increase the practicality for the various tasks.

The HIT-UAV dataset includes 2898 infrared thermal images extracted from 43470 frames, ensuring the valid image data and filtering the consecutive frames with little difference in features. The whole images have object annotations and flight data. Each object bounding box has two types, oriented and standard, annotated by hand. The oriented bounding box can solve the issue that object instances have a significant overlap in aerial images. The standard bounding box promotes developers and researchers efficiently utilizing the dataset on different tasks. The objects of the HIT-UAV dataset have five categories, including Person, Car, Bicycle, OtherVehicle, DontCare, of which the total number is 24899. Note that the meaning of the category DontCare is that there are meaningful objects in this region, but the annotator cannot identify their classes (see section 3 for details). The HIT-UAV dataset is split into 2029 training images and 579 test images and 290 validation images. In order to evaluate the HIT-UAV dataset, we trained and tested the representative test images and 290 validation images. In order to evaluate the performance of representative object detection algorithms (YOLOv4 and YOLOv4-tiny) to evaluate the practicality of the HIT-UAV dataset and analysis the reason why the infrared thermal dataset can help algorithms achieve more excellent performance than the visual light dataset. In section V, we conclude the paper.

II. RELATED WORK AND MOTIVATION

Motivated by the deep learning technique, the area of object detection has developed rapidly in recent years. Large datasets for object detection have promoted the development of object detection applications. PASCAL VOC dataset is the classic object detection dataset, which has two versions, 2007 and 2012. There are 21503 images and 20 categories for object detection in the two versions. Because of the inadequate number of images, PASCAL VOC is unsuitable for handling most detection needs. Therefore, MSCOCO and ImageNet are favored by researchers as the benchmark to evaluate object detection algorithms due to the large numbers of images. Unlike natural environments, aerial images contain more object instances due to the wider view, which brings more significant challenges. In aerial images, objects are much smaller than natural images. The Figure 3(a) and the Figure 3(b) show the difference between natural environment image and aerial image. Table I demonstrates the difference between aerial images and natural images. In Table 1, Avg. Bbox quantity denotes the average bounding box quantity per image. Compared with PASCAL VOC, MSCOCO and ImageNet, the HIT-UAV dataset has a higher average number of bounding boxes.

With the development of AI and application of UAVs for different domains such as forest fire prevention, traffic surveillance, disaster relief and package delivery, many datasets of aerial perspective were introduced for the AI task with UAV platform. Stanford

| Dataset              | Avg. Bbox quantity |
|----------------------|--------------------|
| PASCAL VOC (07+12)   | 2.89               |
| MSCOCO (2014 trainval) | 7.19              |
| ImageNet (2017 train) | 1.37               |
| HIT-UAV             | 8.59               |
TABLE II
COMPARISON WITH EXISTING UAV DATASET INFORMATION

| Dataset | Data type       | Object annotation | Visual data | Altitude | Camera perspective | Infrared thermal |
|---------|-----------------|-------------------|-------------|----------|--------------------|------------------|
| Stanford [20] | real            | yes               | yes         | no       | no                 | no               |
| UAV123  [15]    | synthetic/real  | yes               | yes         | no       | no                 | no               |
| CARPK   [11]     | real            | yes               | yes         | no       | no                 | no               |
| VisDrone [23]   | real            | yes               | yes         | no       | no                 | no               |
| AU-AIR  [3]      | real            | yes               | yes         | yes      | no                 | yes              |
| ASL-TID [17]    | real            | yes               | yes         | no       | no                 | yes              |
| BIRDSAI [12]    | synthetic/real  | yes               | yes         | no       | no                 | yes              |
| FLAME  [22]     | real            | no                | yes         | no       | no                 | yes              |
| Paper   [13]     | real            | yes               | yes         | yes      | yes                | yes              |

HIT-UAV | real | yes | yes | yes | yes | yes

(a) synthetic scene of UAV123 dataset.  
(b) low-altitude natural scene.  
(c) high-altitude natural scene.

Fig. 2. Sample images of the different scenes.

Drone dataset [20] was introduced for human trajectory understanding. It annotated Pedestrians, bicycles, skateboards, cars, and buses, which can also be used for object detection and object tracking tasks. However, the UAV altitude, camera perspective, and background changes are small because UAV record video at a fixed point, which makes the insufficient diversity of the dataset. The UAV123 dataset [15] has more different scenes for object tracking in UAVs. However, it captured videos from a low-altitude aerial perspective and contained some synthetic scenes. Figure 2 shows the examples of UAV images in the synthetic scene, natural low-altitude scene, and natural high-altitude scene. Compared with natural scenes, the synthetic scenes have more minor lighting variations and scene detail, which may lead to poor detection performance in natural scenes. Compared with the low-altitude perspective, the high-altitude perspective can detect more objects and enable the UAV to scan a larger area. The UAVs flying at higher altitudes have the advantage of accessibility in the city with tall buildings. The above advantages indicate that high-altitude datasets are beneficial to applying UAVs in practical tasks. For the car detection task, the CARPK [11] dataset contains nearly 90000 cars from 4 different parking lots. Because the dataset introduces for object counting, it only contains one category (car) and one altitude (40 meters), limiting its application area. The VisDrone dataset [27] contains large data for object detection and object tracking. It covers a wide range of aspects, including location, environment, objects, and density. Although VisDrone is excellent, it still has the disadvantage that it did not label altitudes and camera perspectives. This disadvantage makes VisDrone unable to apply it to particular areas, such as researching the influence of different altitudes on object detection accuracy. The AU-AIR dataset [3] can be applied to some particular tasks because it provided more flight data such as flight altitude, GPS data, IMU data, etc.

The above UAV datasets are based on the visual light camera. With the development of the thermal infrared camera, its image quality and resolution have improved [9]. The main advantages of thermal infrared cameras are there can capture images in total darkness and less intrusion on privacy, which can be applied to rescue and surveillance systems during the night. The ASL-TID dataset [17] is a thermal-based UAV dataset for object detection and tracking. The sample image is shown in Figure 3(c). Its disadvantages are obvious. First, its flight altitudes range from 10 to 30 meters, making it unusable for high-altitude missions when most urban buildings are higher than 30 meters. Second, it just contains 13 scenes with almost unchanged backgrounds, making it unable to perform well in other scenes. Third, it has one or no object instance in most images, which leads to low data complexity. The BIRDSAI dataset [2] introduced the aerial thermal infrared videos for detection and tracking in multiple African protected areas. The sample image is shown in Figure 3(d). The detection objects of BIRDSAI are animals and humans. The FLAME dataset [22] introduced a forest fire dataset for classification and semantic segmentation, including thermal infrared videos and visual light videos. The sample image is shown in Figure 3(e). Minglei Li et al. [13] proposed a low-altitude thermal infrared dataset for saliency map because the authors found there is no publicly available thermal dataset for pedestrians and vehicles from the perspective of UAV. The sample image is shown in Figure 3(f). Compared to the HIT-UAV dataset, it contains few objects in the image due to the lower altitude.

In response to the flaws of the above UAV datasets, we present the first publicly available high-altitude thermal
infrared dataset for pedestrians and vehicles, the HIT-UAV dataset. It covers a wide range of aspects, including location (schools, parking lots, roads, playgrounds, etc.), objects (person, car, bicycle, etc.), times (night, day), altitudes (from 60 to 130 meters), camera perspectives (from 30 to 90 degrees), and infrared thermal images. Table II demonstrates the difference between HIT-UAV dataset and other UAV datasets.

The HIT-UAV dataset has the advantages as follows:

- **Privacy advantage.** As shown in Figure 3(g), the person in HIT-UAV is shown as a white block. There is no personal appearance, clothing, or even gender information in the image, fully protecting individual privacy.

- **Detection accuracy advantage.** The infrared thermal camera uses infrared information to capture images, reducing the complexity of the image information while improving privacy. This feature reduces the search space of the neural network, improving the detection accuracy in Infrared thermal scenes. The HIT-UAV dataset contains 2898 images extracted from 43470 frames, ensuring valid image data and filtering the consecutive frames with little difference in features. Section IV evaluates the detection performance using the HIT-UAV dataset, showing the detection accuracy advantage compared visual light aerial dataset.

- **Night detection advantage.** As shown in Figure 4 it shows the images captured by the visual light camera and the infrared thermal camera at the same flight altitude and camera angle at night. We can quickly identify the car and bicycle objects in the infrared thermal image. However, it is tough to identify the objects in the visual light camera image. Therefore the infrared thermal camera can help UAVs perform tasks better at night. Note that the detection range of the infrared thermal camera is less than the visual light camera due to the longer focal length of the infrared thermal camera, which indicates that UAVs with the infrared thermal camera should have a higher flight altitude to promote the detection range. It proves the dataset with high altitude is valuable and necessary.

The HIT-UAV dataset has the great potential to enable several research activities, such as (1) the application range of the infrared thermal and visual light camera in object detection tasks, (2) the feasibility of UAV search and rescue missions at night, (3) the relationship of flight altitude and UAV object detection precision, (4) the impact of camera perspective on UAV object detection, and so on.

III. HIT-UAV

A. Hardware setup

This paper selects DJI Matrice M210 V2 as the hardware platform to collect data. The price of DJI Matrice M210 V2 is about 10000 US dollars. The setup of DJI Matrice M210 V2 is shown in Table III.

We have used the DJI Zenmuse XT2 camera loaded on the UAV to capture the images. DJI Zenmuse XT2 camera features a FLIR longwave infrared thermal camera and a visual camera, the thermal infrared camera at 640 × 512 resolution and 25mm lens; the visual camera captures 4K
TABLE III
THE SETUP OF DJI MATRICE M210

| Dimensions       | Unfolded, 883×886×398 mm; Folded, 722×282×242 mm |
|------------------|---------------------------------------------------|
| Diagonal Wheelbase| 643 mm                                             |
| Weight           | Approx. 4.8 kg (with two TB55 batteries)           |
| Max Takeoff Weight| 6.14 kg                                            |
| Max Payload      | 1.34 kg                                            |
| Max Angular Velocity| Pitch: 300°/s, Yaw: 120°/s                       |
| Max Ascent Speed | 16.4 ft/s (5 m/s)                                  |
| Max Descent Speed| (vertical) 9.8 ft/s (3 m/s)                        |
| Max Flight Time  | S-mode/A-mode: 73.8 kph (45.9 mph); P-mode: 61.2 kph (38 mph) |
|                  | (with two TB55 batteries) 34 min (no payload); 24 min (takeoff weight: 6.14 kg) |

videos and 12MP photos. The price of the DJI Zenmuse XT2 camera is about 8000 US dollars.

B. Data description
The HIT-UA V dataset collected 43470 original frames. However, there is a slight variation in image features between consecutive frames. Therefore, most of the frames cannot help much to improve the detection performance of the object detection model. Many datasets reserve full frames to train detection models, which doesn’t solve the problem that the distribution of features is limited. The HIT-UA V dataset has a lot of original frames, and it is collected in schools, parking lots, roads, playgrounds, etc., guaranteeing it has the features of many scenes. We sample an image every 15 frames (the video refresh rate is 7 FPS) to filter adjacent frames with little difference. Then we got 2898 infrared thermal images. The resolution of images is 640×512 pixels, and images record the date, weather, altitude, and camera perspective. For annotation files, we provide two types of files (JSON file and XML file) to facilitate developers’ use. For the name of the images file, the format is $T_HH(H)_{AA_W}NNNNN$, where $T$ denotes the shooting times (the day is 0 and the night is 1), $HH(H)$ denotes the flight altitudes (from 60 to 130 meters), $AA$ denotes the perspective of the camera (from 30 to 90 degrees), $W$ denotes the weather (only no rain weather be collected currently), $NNNNN$ denotes the serial number of image.

C. Annotation method
All objects in the HIT-UA V dataset are manually annotated. In the object detection task, objects are annotated with bounding boxes. The common representation of the bounding box is $(x_c, y_c, w, h)$, where $x_c, y_c$ denotes the center coordinate, $w$ and $h$ denote width and height of the bounding box, respectively. However, in the perspective of UAVs, objects in aerial images cannot be accurately labeled. We used $\theta$-based oriented bounding box [26] to label object instances. The oriented bounding box is $(x_c, y_c, w, h, \theta)$, where $\theta$ denotes the oriented angle from the horizontal direction of the standard bounding box. As shown in Figure 5 (a), the overlap of the standard bounding box is so significant that the state-of-the-art object detection algorithms cannot distinguish them well. The method of oriented bounding box can accurately annotate the object to solve the above issue as shown in Figure 5 (b). Note that the bounding box on the boundary is standard because the oriented bounding box cannot exceed the edge. A flaw of the oriented bounding box is that few native object algorithms support training it. Therefore, we provided oriented bounding box and standard bounding box annotation files.

D. Properties
The annotated object categories include four types of objects which highly appear in rescue and search missions: Person, Car, Bicycle, OtherVehicle. In addition, we labeled unrecognizable objects, namely DontCare, because many objects cannot identify specific types by annotator in high aerial images. As shown in Figure 6 the red box represents the object of DontCare. In the object area, we cannot identify if they are persons. Therefore, the DontCare label can point out easily confused objects in the image.

Figure 7 shows the distribution of annotations cross object categories. The main object for the rescue mission (Person) appears significantly more than other objects. The Car and
Bicycle objects also have a large proportion in the dataset, allowing the HIT-UAV dataset for many common tasks. In order to increase the adaptability of high-altitude missions, we recorded data from 60 to 130 meters every 10 meters for flight altitude. Figure 8 shows the distribution of flight altitudes. The angle data of the camera was recorded from 30 to 90 degrees every 10 degrees to provide images from different perspectives. Figure 9 shows the distribution of camera perspectives. Infrared thermal images have a significant difference between day and night due to the higher background temperature during the day. As shown in Figure 10, the infrared thermal image during night finds the object more easily than during the day because the background temperature of the night is lower than a day. We collected the infrared thermal images in day and night to increase the diversity of the dataset. Figure 11 shows the distribution of images for day and night.

IV. EVALUATION AND ANALYSIS

We trained and evaluated object detection algorithms on the HIT-UAV dataset. Considering YOLO has been widely used in many actual applications, we choose YOLOv4 and YOLOv4-tiny to train and evaluate. The number of training images is 2029, the number of validation images is 290, the number of test images is 579. The GPU of training is RTX 2080Ti and uses the original darknet framework to train the model. Moreover, as shown in Table IV we show the precision of YOLOv4 and YOLOv4-tiny trained the COCO dataset and best accuracy of object detection algorithms with VisDrone-2019 challenge [28].

For the results of the HIT-UAV dataset, we observe that the AP value of Person is significantly lower than other categories with YOLOv4-tiny. This might happen because the detection ability of YOLOv4-tiny for tiny objects is lower than YOLOv4. The AP value of OtherVehicle does not achieve a good score, which might happen due to the categories imbalance problem.

In the VisDrone-2019 challenge, the best precision is 55.82% AP50 achieved by the RRNet method. The original YOLOv4 can achieve 65.70% AP50 in COCO higher than RRNet in VisDrone, which shows that aerial image information is more complicated than natural image. For the HIT-UAV dataset, the original YOLOv4 achieve 84.75% AP50 in the test set.

The above results indicate the observations as follow:

- Infrared thermal images filter a lot of irrelevant information, making the objects easier to identify.
- Infrared thermal images can help the common detection model achieve excellent detection performance without many images because the objects of the infrared thermal image have easily recognizable features. The HIT-UAV dataset can contribute to detecting vehicles and persons...
TABLE IV
THE AVERAGE PRECISION OF THE BASELINE MODEL

| Model       | Dataset | Person | Car  | Bicycle | OtherVehicle | AP50  |
|-------------|---------|--------|------|---------|--------------|-------|
| YOLOv4      | HIT-UAV | 89.88% | 92.64% | 86.48% | 69.99%       | 84.75%|
| YOLOv4-tiny | HIT-UAV | 16.86% | 83.61% | 51.90% | 49.17%       | 50.38%|
| YOLOv4      | COCO    |        |       |         |              | 65.70%|
| YOLOv4-tiny | COCO    |        |       |         |              | 40.20%|
| RRNet       | VisDrone-2019 |     |       |         |              | 55.82%|

Fig. 11. Distribution of images across flight times.

The sample detection results of the baseline model trained on the HIT-UAV dataset are shown in figure [12]. We can observe that the model has good to capture the objects in infrared thermal aerial images. We hope the HIT-UAV dataset can promote the development of drone-based object detection tasks.

V. CONCLUSION

This work presents the HIT-UAV dataset, a high-altitude infrared thermal UAV dataset for object detection. The HIT-UAV dataset records different flight data, including flight altitude, camera perspective, time, date, etc., to help various researchers focus on different research aims.

The UAVs loaded with the infrared thermal camera have many advantages for detection applications. The infrared thermal camera can clearly capture the objects in total darkness and promotes privacy in detection applications. We train and evaluate YOLOv4 and YOLOv4-tiny with the HIT-UAV dataset. The results show that infrared thermal images filter a lot of irrelevant information to make the objects more straightforward to identify than visual light images, significantly promoting the detection ability of detection algorithms. These advantages greatly enhance the feasibility of UAV automatic object detection in many important tasks at night. We hope the HIT-UAV dataset can contribute to different UAV applications such as night person search and rescue, night traffic surveillance, night city monitoring, etc.

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