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METHODOLOGIES AND APPLICATION

UAVData: A dataset for unmanned aerial vehicle detection

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Abstract
The unmanned aerial vehicles (UAVs) significantly contribute to the convenience and intelligence of life. However, the large use of UAVs also leads to high security risk. Only detecting the small and flying UAVs can prevent the safety accidents. UAV detection task could be regarded as a branch of object detection in flied of image processing. The advanced object detection models are mainly data driven, which depend on large-scale databases. The well-labeled datasets have proved to be of profound value for the effectiveness and accuracy in various object detection tasks. Thus, the first step of detecting UAVs is to build up a dataset of UAVs. In this study, we collect and release a dataset for UAV detection, called UAVData. To maintain the universality and robustness of the trained models, balloons and 6 types of UAVs are recorded in the dataset which totally consists of 13,803 well-labeled and recognizable images. We further conduct strong benchmarks using several advanced deep detection models, including faster R-CNN, SSD, YOLOv3. In addition, we utilize 4 different convolutional neural network models as the backbone models of these object detection methods to learn UAV-related features in images. By providing this dataset and baselines, we hope to gather researchers in both UAVs detection and machine learning field to advance toward the application.

Keywords Object detection · UAV detection · UAV image dataset · Convolutional neural network

1 Introduction

With the development of science and technology, unmanned driver products have brought a lot of convenience to people's life. Due to the cheapness and the availability, unmanned aerial vehicles (UAVs) have been widely applied in both practical military and civilian areas. For example, UAVs are used to help transport and fire control. The Federal Aviation Administration (FAA) noted that the purchases of drones have more than doubled in 5 years, i.e., from 1.9 million in 2016 to 4.3 million by 2020 (Wargo et al. 2016). However, the extensive use of UAVs has also brought various bad effects, such as public safety and personal privacy (Wu et al. 2018). Therefore, it is necessary to regulate and manage the flight of UAVs that premised on the detection. One way is to detect UAVs by applying radar and infrared (Mohajerin et al. 2014; Torvik et al. 2016; Park et al. 2019; Kim et al. 2016; Sosnowski et al. 2018; Ryu et al. 2018). Although radar and infrared equipment have high-distance accuracy and all-weather adaptation, their high cost and poor flexibility are inconsistent with the increasing requirement of UAV detection. Accordingly, the more inexpensive and convenient sensors, e.g. cameras, have attracted increasing attention in decades (Krizhevsky et al. 2012), which become the better equipment to detect UAVs.

UAV detection by cameras is to localize and classify the UAVs in images, which belongs to computer vision context and is regarded as an object detection problem. Since the big success of deep learning in image process (He et al. 2016;

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Girshick et al. 2014), nature language processing (Abualigah 2019; Yang et al. 2019) and optimization (Abualigah and Diabat 2020; Abualigah 2020; Abualigah et al. 2020), object detection is recently addressed by deep neural networks. Object detection is to localize and classify the objects in images. For example, the output of an object detection method is the bounding box coordinates and the classification results of the objects in the input images. Because of the two tasks of object detection, the object detection model mainly consists of backbone model and detection head. The backbone model is to extract the feature from images. Many studies have pointed out the effectiveness of convolutional neural networks (CNNs) on object detection tasks as backbone models (Girshick et al. 2014; Girshick 2015; Ren et al. 2015; Liu et al. 2016; Redmon et al. 2016; Redmon and Farhadi 2017, 2018). The detection head is to find out the classification and localization feature of objects. The detection head of existing object detection could be divided into categories:

- One-stage methods: these kinds of methods jointly predict the probability of category and locate bounding boxes for objects, such as SSD (Liu et al. 2016) and YOLO (Redmon et al. 2016; Redmon and Farhadi 2017, 2018).
- Two-stage methods: classification and localization tasks are not parallel. These methods need select region proposals firstly, and then the selected regions are classified, like R-CNN (Girshick et al. 2014), fast R-CNN (Girshick 2015), faster R-CNN (Ren et al. 2015).

However, almost object detection methods are data driven and depend on large-scale well-labeled dataset (Lin et al. 2014; Everingham et al. 2010). Moreover, there is few open released datasets and benchmarks for the UAV detection tasks, limiting the development of it. In this study, we focus on building an image dataset named UAVData, consisting of 11666 UAVs images, 2137 balloon images and 7 test video sequences. To increase diversity, the UAVs used in the UAVData are with different patterns and the balloons are distinct in colors. We manually annotated all images with categorical labels and bounding boxes labels. It makes that the dataset could be applied to both UAV detection and flying objects detection tasks.

We conducted extensive qualitative and quantitative analysis on the proposed dataset. For references, we evaluated several advanced object detection frameworks, including SSD (Liu et al. 2016), YOLOv3 (Redmon and Farhadi 2018) as well as faster R-CNN (Ren et al. 2015), making the baselines convinced. Moreover, we utilize 4 different CNN models, VGG, ResNet, DarkNet and DenseNet, as the backbone of these object detection methods to learn more UAV-related features in images.

These models achieve high results in both UAV detection and flying objects detection tasks. The results reveal that our dataset is essential for these tasks. On the model side, although the methods yields comparable accuracy, YOLOv3 model has the fastest speed and best accuracy, which performs an important role in real-time UAV detection tasks.

Our contributions are mainly in two fields,

- Deep learning-based method is one of the most effective ways for object detection. It also an effective method to realize UAV detection which is a branch of object detection. However, the success of deep learning-based method depends on large-scale data. The lack of UAV image data limits the development of UAV detection. Thus, our work, a large-scale image dataset, provides data support for UAV detection, which is novel and significant. The details, labelling methods and applications are introduced in Sect. 3.
- We apply some widely recognized object detection methods, such as SSD, YOLOv3 and faster R-CNN, to UAV detection. In order to extract more feature from images than these baseline model, CNN models (VGG, ResNet, DarkNet and DenseNet) are utilized as the backbone of these baseline models. The results of these detection models are provided in Sect. 4.

2 Related work

In this section, we review the related studies on UAV detection.

2.1 The image datasets

Datasets are the most important resource in every field of research, and they can promote the development of one field. There already exist some drone datasets, which are adapted for UAVs detection. However, most of them are either private or have only a small amount of data.

The Anti-drone Dataset The Anti-drone Dataset (Wu et al. 2018) is a not public drone dataset including three drone models with 49 experiments videos. The frame resolutions in main stream and sub stream are 2048×1537 and 1024×768, respectively. All the video is annotated by the KCF tracking algorithm (Henriques et al. 2015).

The USC-GRAD-STDdb The Small Target Detection database (USC-GRAD-STDdb) (Bosquet et al. 2018) is a set of annotated video for small target detection. Small objects (drone, boat, vehicle, person, bird) are 16–256 pixels in size of an image with 1270×720 pixels. The USC-GRAD-STDdb is one of the few public datasets with drone images. However, the dataset focus on small objects which are hard for people to recognize.

Next, some notable datasets are introduced, which have been widely utilized for image classification, object recognition task etc.. These large-scale datasets are public and popular in computer version field, but they focus on many objects, not the drones.

Microsoft COCO The Microsoft COCO dataset (Lin et al. 2014) is a large, public and popular dataset for object recognition. The dataset contains 91 objects types with a total of 328k images and 2500k labels. Like most object recognition datasets, COCO also focus on (1) image classification, (2) object bounding box localization and (3) semantic segmentation. Specially, objects are labeled using per-instance segmentation for precise object localization.

The Pascal VOC The Pascal VOC dataset (Everingham et al. 2010) was from the VOC challenges 2005–2012 which provided well-labeled image data sets for object category recognition. The dataset has served as training and evaluation benchmarks for most of today's computer version algorithms including 20 objects types (like person, bird, cat, aeroplane, bicycle, bottle, chair) with 9963 images (VOC 2007) and 11,540 images (VOC 2012).

ImageNet ImageNet Large-Scale Visual Recognition Challenge (ILSVERC), an image classification and object detection challenge, has been held every year since 2010. The ImageNet dataset (Deng et al. 2009) of the challenge contains more than 14 million images, covering more than 20k categories. More than a million of these images are clearly labeled with category and bounding box information.

In general, the public UAV datasets are few. In order to solve this problem, it is necessary to establish a public UAV-related dataset.

2.2 UAV detection

Recently, radar, infrared, optical and acoustic equipment are widely used to track UAVs. Based on the different source of data, drone detection methods could be divided into 4 types: (1) radar-based method, (2) infrared-based method, (3) sound-based method and (4) vision-based method.

Among them, methods based on radar and infrared are more popular because of their ability to work long time regardless the weather. For radar-based detection methods (Mohajerin et al. 2014; Torvik et al. 2016; Park et al. 2019), in order to recognize UAVs from other flying objects, radar was used to track the objects and then the flying trajectory, the velocity and the distance information were extracted from the echo signals of the radar. Then, those information was analyzed through numerical simulation and experiments to distinguish UAVs and other flying objects. Infrared search and tracking is a popular method for detection, tracking and identification problem (Infrared and electro-optical systems handbook 1993). The infrared system was utilized to gain data of UAVs which would be used to train a detector to locate and recognize the UAVs (Sosnowski et al. 2018; Ryu et al. 2018).

However, their high cost and poor flexibility are inconsistent with the increasing requirement of UAV detection. With the development of science and technology (Arqub and Al-Smadi 2020; Arqub et al. 2016, 2017; Arqub and Abo-Hammour 2014), many difficult problems have multiple solutions. For UAV detection, the more inexpensive and convenient sensors are the better choice. For example, based on the images and sound of the UAVs to detect UAVs Sound-based detection methods (Jeon et al. 2017; Mezei and Molnár 2016) were firstly collect sounds of drones in complicated environments which maybe cover sounds from multiple objects. Then, the acoustic models were used to distinguish the sounds of drones from other noise.

Compared with sound-based detection methods, vision-based detection methods are more intuitive and easier to understand. Vision-based detection focused on the vision data like images and videos. The study (Schumann et al. 2017) proposed an UAVs detection framework based on videos. In this study, region proposals were firstly selected by using median background subtraction or a deep learning method, respectively. Then, a CNN was applied as a classifier to identify UAVs or distractors. Another image-based method (Wu et al. 2018) designed a real-time drone detector by using deep learning method. The Yolo method was modified to adapt for UAV detection. The study also built their own image dataset, and the detector was verified among extensive experiments. However, it only transformed the Yolo method and ignored other object detection methods and the characteristics of UAV in images.

3 The UAVData

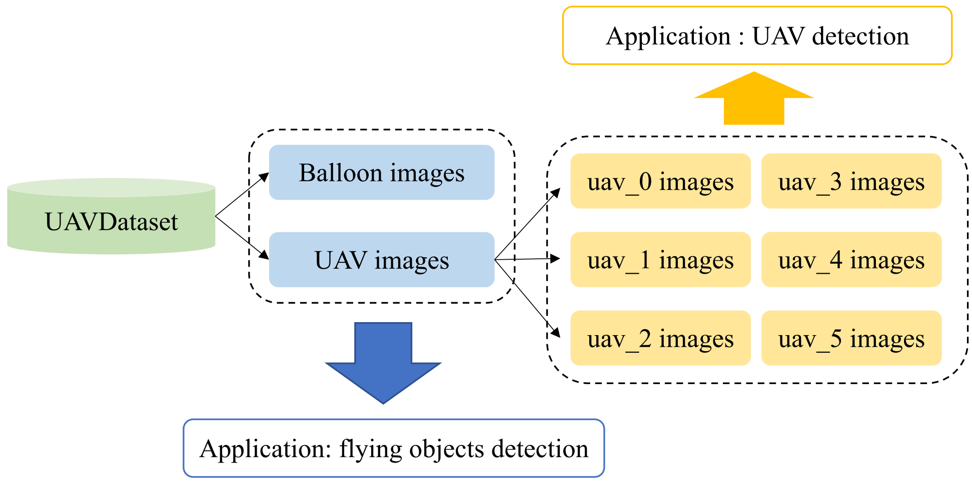
Prior studies have shown the importance of the open released dataset for training and testing an object detection model. In this study, we focus on UAV detection task that urgently needs to be addressed and build up a well-labeled UAV image dataset to provides data support of it. We manually collect and label UAV images, and then construct the new dataset, namely UAVData.[1] In the procedure, we also collect images of balloons which are treated as distractors for the UAVs, thus to introduce noise into the data. In order to maintain the universality of the trained models, the six types of UAVs and 5 colors of balloons are recorded, shown as Fig. 1.

3.1 Collection of images

We have carried on a large amount of manual work to complete the UAVData. To simplify the procedure, we first

[1] https://github.com/ZengYuni/UAVData/.

Fig. 1 Illustration of UAVData



shoot videos of various UAVs and balloons, then frames are extracted from the videos. Considering the real-world challenges, the recording environments includes rapid light changes, complex scenarios, as well as the blurring caused by high-speed motion. We make a consistency by applying Sony $AF4132X$ recorder and resize each image to the resolution of 1280×720. The part of blurred and non-object images are discarded; thus, we finally extracted 13,803 images from the videos. All photos are manually annotated with precise bounding boxes and categories of objects. Moreover, we shoot 7 extra videos which are regarded as validation and testing data.

Fig. 2 UAVs in the UAVData dataset

3.2 Properties of UAVData

Specifically, the proposed database considers 6 kinds of widely used drones, the images of which are shown in Fig. 2 ($UdiR/C : U919A$, $TheNorthEhome : AG-01D$, $ATTOP : XT-1$, $HR : sh5$, $ATTOP : YD615$, $MI : YKFJ01FM$). As seen, both quadcopter and helicopter are considered, making a good coverage on the variants of UAVs. Note that, the quad-copters have distinct characteristics, e.g., exclusive colors and shapes. Concerning the jamming objects, the balloons recorded in the dataset are the commonly used ellipsoid shape with five colors, i.e., red, yellow, black, green and purple.

In order to increase the complexity of our database, videos are recorded in different scenes, such as blank background, workshop, laboratory, and outdoor scenes with sky, trees, buildings. The parts of images in our UAVData are shown in the following figures, specially uni-drone images (only one drone per image) in Fig. 3, multi-drone images (multiple drones per image) in Fig. 4 and balloon images in Fig. 5. Each balloon image contains a variable number of balloons with varying sizes.

Totally, 13,803 images are extracted, and every target (drone or balloon) in images has a corresponding bounding box and the number of which is the number of times the targets appear. The UAVData contains 7320 uni-drone images, 4346 multi-drone images and 2137 balloon images.

The distribution of uni-drone images and pixels of the drones is concluded in Table 1, and that of multi-drone images is listed in Table 2. From the both tables, it is clear that the occupied area of drones is a small part of the whole image with the resolution of 1280×720.

Moreover, we shoot and annotate 7 videos as the test sequences, including: (1) 6 uni-drone videos that cover the movements of each drone and last 150 s in average and (2) 1 multi-drone video that record the scenes of multiple drones appearing at the same frame with 64 s.

3.3 Applications of UAVData

Flying Objects Detection Nowadays, not only birds and aircraft but also unmanned drones ranging from relatively large UAVs to much smaller consumer drones are frequently seen in the sky. Flying objects (drones, birds, and so on) need to be detected to avoid collisions, and the ability to detect by inexpensive and light sensors such as cameras for collision-avoidance purposes becomes increasingly important (Rozantsev et al. 2017). In this application, UAVData could be used for training a detector which is to localize

Fig. 3 Parts of uni-drone images in our UAVData

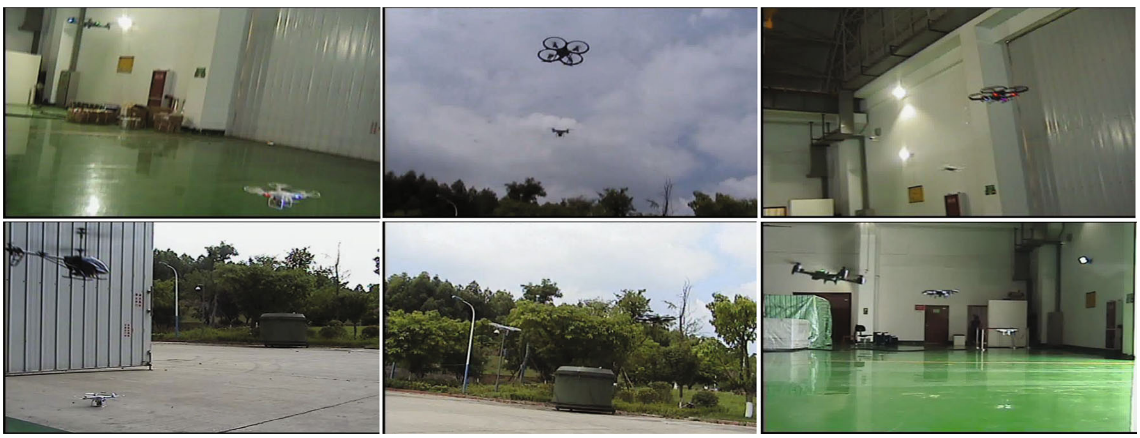


Fig. 4 Parts of multi-drone images in our UAVData

Fig. 5 Parts of balloon images in our proposed dataset

Table 1 Distribution of uni-drone images

Annotation	Total of bounding boxes	Maximum pixels of target	Minimum pixels of target
uav_0	3238	577×301	65×21
uav_1	3316	720×303	60×24
uav_2	2461	644×266	60×20
uav_3	2355	570×267	61×35
uav_4	2174	485×234	55×46
uav_5	2126	484×208	57×18

Table 2 Distribution of multi-drone images

Annotation	Total of bounding boxes	Maximum pixels of target	Minimum pixels of target
uav_0	1640	476×198	75×22
uav_1	2010	824×283	45×23
uav_2	1276	354×189	64×14
uav_3	1348	594×281	59×24
uav_4	879	483×186	47×47
uav_5	1051	460×220	39×23

and recognize flying objects when those flying objects only occupy a small portion of the field of view. The images of those flying objects are 1280×720 resolution with bounding boxes and precise categories. The UAVData covers different flying objects, like UAV and balloon, and the distribution of images for flying detection is shown in Table 3. The occupied area of those small flying objects are also provided in the table.

UAVs detection In this application, the UAVData is utilized to train a real-time detector with universality and robustness. Due to the real-time property of drone detection, it is important to speed up the model rather than improve the accuracy. Therefore, with total of 11,666 images using as training data, the UAVData also contains 7 video sequences as testing data. In the images and video sequences, 6 different drones are recorded and the distribution of training data for drone detection is listed in Table 4.

4 Experiments

In this section, we conduct the experiments of the two applications on the multi-drone video and all experiments are conducted on Intel i7-7800x CPU and GTX 1080Ti GPU. The evaluation metrics used in this paper are (1) mean average precision (mAP) which is a widely used evaluation metric in object detection filed because the ability to measure the performance of the localization and classification, (2) frames per second (fps) to measure the speed of models.

4.1 Backbone and detection head

Most object detection methods include two parts: (1) a backbone model as the feature extractor to extract feature from images and (2) a detection head as the detector to find out the classification and localization feature of objects, shown as Fig. 6.

Usually, the backbone models are based on CNNs models. CNN is a class of deep learning networks that are designed to recognize patterns directly from pixel images (LeCun et al. 1998). CNNs always contains two basic operations, namely convolution and pooling. The convolution operation employs multiple filters to extract features (feature map) from images, through which the spatial information in the images can be preserved. The pooling operation, also called subsampling, is utilized to reduce the dimensionality of the feature maps but retains important information of. CNNs have led to a series of significant achievements in image processing, like VGG (Simonyan and Zisserman 2015), ResNet (He et al. 2016), DarkNet (Redmon et al. 2016), and DenseNet (Huang et al. 2017). Nowadays, most object detection models are based on CNNs to extract feature of inputs. In this study, we unitize the advanced CNN models, VGG, ResNet, DarkNet, DenseNet as the backbone of these object detect methods, SSD (Liu et al. 2016), YOLOv3 (Redmon and Farhadi 2018) and faster R-CNN (Ren et al. 2015) to extract UAV features in images. The baseline models are listed in Table 5,

4.2 Flying objects detection

For flying objects detection, we train a detector to localize and identify drones and balloons. We select 30% images randomly as test data and others are used to train the detector.

Table 3 Distribution of images for flying objects detection

Annotation	Total of bounding boxes	Maximum pixels of target	Minimum pixels of target
Balloon images	2137	722 × 755	10 × 12
UAVs images	2032	429 × 198	50 × 24

Table 4 Distribution of training data for UAVs detection

Annotation	Total of bounding boxes	Maximum pixels of target	Minimum pixels of target
uav_0	2328	577 × 301	65 × 21
uav_1	3316	824 × 283	45 × 23
uav_2	2461	644 × 266	64 × 14
uav_3	2355	594 × 281	59 × 24
uav_4	2174	485 × 234	47 × 47
uav_5	2126	460 × 220	39 × 23

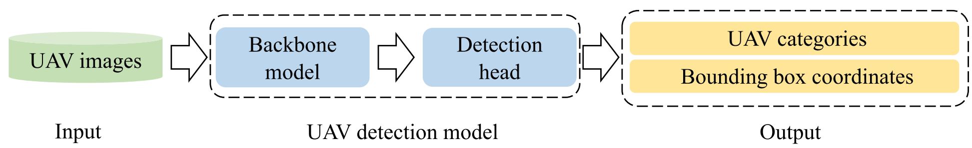


Fig. 6 Procedure of UAV detection

Table 5 Baseline object detection methods of UAV detection

Method	Backbone	Detection head
SSD	VGG-16	One-stage
Faster R-CNN	VGG-16	Two-stage
Yolov3	DarkNet-53	One-stage

The results of faster R-CNN, YOLOv3, SSD with various CNNs frameworks are listed in Table 6. We try to train object detectors using Faster R-CNN. However, the training process failed to converge for the DenseNet, which is also happened other studies, like (Shen et al. 2017).

Speed of detection When the detector is based on VGG-16, the fps result of the YOLOv3 model is higher than that of SSD model which is also higher than that of faster R-CNN model. Not only that, the same results were obtained when the backbone is one of ResNet-50, DarkNet-53, or DenseNet-201. Thus, we can easily find out that the YOLOv3 is the best detection head for detecting small and flying objects among those models in speed of detection.

Performance of detection From Table 6, firstly, for the same detection head, the Resnet-50 is the best backbone of SSD while VGG-16 has the best performance for faster R-CNN and Darknet-53 is the best backbone of Yolov3. Secondly, as for the detection head, the Yolov3 is always the best detection head since it achieve the highest result at 90.8% mAP.

In general, no matter which of these models has the better results, these results in Table 6 are reasonable high results for object detection task. This shows that our data set is essential to the field of flying object detection. Moreover, the CNN models also make contribution to flying object detection for baseline models.

4.3 UAVs detection

In this experiments, we train a detector to localize and identify 6 kinds of small and flying drones. The total of 11666 images of drones to train the detector, and we evaluate on the video sequence with multiple drones. The results of faster R-CNN, YOLOv3, SSD and the models with various CNNs frameworks on the video with multiple drones are listed in Table 7.

Speed of detection It is clear that, despite different feature extractors, the fps results of the YOLOv3 is always the best comparing with faster R-CNN and SSD in UAV detection.

Performance of detection Also, for the same detection head, the Resnet-50 gets the best result for SSD while Darknet-53 is the best backbone for faster R-CNN and Yolov3. In addition, as for the same backbone, SSD is the best detection head for VGG-16 and Resnet-50 while Yolov3 has the best performance for Darknet-53 and Densenet-201 in UAV detection task.

All in all, on the UAV detection task, whichever model has the best results in terms of speed and accuracy, these widely recognized object detection methods have a reasonable and accurate result on our dataset. This is enough to show that our dataset provides data support for UAV detection. In addition, the CNN models of these detection methods have indeed helped the baselines to achieve better results in speed or mAP.

Table 6 Results of flying objects detection

Detection head	Backbone	Input size	Speed (fps)	mAP (%)
SSD	VGG-16	300 × 300	42	74.2
	ResNet-50	300 × 300	22	75.3
	DarkNet-53	300 × 300	24	74.8
	DenseNet-201	300 × 300	14	73.5
Faster R-CNN	VGG-16	600 × 600	11	90.6
	ResNet-50	600 × 600	10	90.4
	DarkNet-53	600 × 600	10	86.3
	DenseNet-201		Failed	
YOLOv3	VGG-16	416 × 416	70	**90.8**
	ResNet-50	416 × 416	**86**	90.6
	DarkNet-53	416 × 416	72	**90.8**
	DenseNet-201	416 × 416	49	90.7

Table 7 Results of UAVs detection

Detection head	Backbone	Input size	Speed (fps)	mAP (%)
SSD	VGG-16	300 × 300	9	87.4
	ResNet-50	300 × 300	12	**88.7**
	DarkNet-53	300 × 300	11	82.8
	DenseNet-201	300 × 300	8	86.8
Faster R-CNN	Vgg-16	600 × 600	12	82.6
	ResNet-50	600 × 600	11	75.8
	DarkNet-53	600 × 600	10	83.0
	DenseNet-201		Failed	
YOLOv3	VGG-16	416 × 416	68	62.7
	ResNet-50	416 × 416	**84**	86.9
	DarkNet-53	416 × 416	71	**88.7**
	DenseNet-201	416 × 416	47	87.9

5 Conclusion and future Work

In the paper, we have established an image dataset for UAV detection task, called UAVData. It contains 13803 images of UAVs and balloon and 7 testing videos. Then, we verify our dataset on two tasks: flying object detection and UAV detection. The widely used object detection methods, SSD, faster R-CNN and YOLOv3, are used as the baseline models. In addition, we apply VGG-16, Resnet-50, Darknet-53 and Densenet-201, as the backbone models of the object detection methods to extract more UAV-related information of images. These models achieve high results in UAV detection task, which reveal that our dataset plays an essential and significant role in UAV detection. We also believe that our dataset could help experts to develop effective methods for UAV detection.

In future work, on the one hand, we plan to collect more type of UAVs and include more information such as description, segmentation. On the other hand, most today's datasets (like PASCAL, ImageNet) for object detection are built in order to contain a large number of images for nearly all object classes rather than focussing on one issue. With the lack of dataset focusing on drone detection, we believe that the high quality and large scale of UAVData will become a new and challenging benchmark dataset for future research.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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