Vision Meets Drones: A Challenge

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Abstract—In this paper we present a large-scale visual object detection and tracking benchmark, named **VisDrone2018**, aiming at advancing visual understanding tasks on the drone platform. The images and video sequences in the benchmark were captured over various urban/suburban areas of 14 different cities across China from north to south. Specifically, **VisDrone2018** consists of 263 video clips and $10, 209$ images (no overlap with video clips) with rich annotations, including object bounding boxes, object categories, occlusion, truncation ratios, etc. With intensive amount of effort, our benchmark has more than 2.5 million annotated instances in $179, 264$ images/video frames. Being the largest such dataset ever published, the benchmark enables extensive evaluation and investigation of visual analysis algorithms on the drone platform. In particular, we design four popular tasks with the benchmark, including object detection in images, object detection in videos, single object tracking, and multi-object tracking. All these tasks are extremely challenging in the proposed dataset due to factors such as occlusion, large scale and pose variation, and fast motion. We hope the benchmark largely boost the research and development in visual analysis on drone platforms.

Index Terms—Drone, benchmark, video analysis, object detection, object tracking

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1 INTRODUCTION

COMPUTER vision has been attracting increasing amounts of attention in recent years due to its wide range of applications and recent breakthroughs in many important problems. As two core problems in computer vision, object detection and object tracking are under extensive investigation in both academia and real world applications, *e.g.*, transportation surveillance, smart city, and human-computer interaction. Among many factors and efforts that lead to the fast evolution of computer vision techniques, a notable contribution should be attributed to the invention or organization of numerous benchmarks, such as Caltech [1], KITTI [2], ImageNet [3], and MS COCO [4] for object detection, and OTB [5], VOT [6], MOTChallenge [7], and UA-DETRAC [8] for object tracking.

Drones (or UAVs) equipped with cameras have been fast deployed to a wide range of applications, including agricultural, aerial photography, fast delivery, surveillance, *etc*. Consequently, automatic understanding of visual data collected from these platforms become highly demanding, which brings computer vision to drones more and more closely. Despite the great progresses in general computer vision algorithms, such as detection and tracking, these algorithms are not usually optimal for dealing with sequences or images captured by drones, due to various challenges such as view point changes and scales. Consequently, developing and evaluating new vision algorithms for drone generated visual data is a key problem in drone-based applications. However, as pointed out in [9], [10], studies toward this goal is seriously limited by the lack of publicly available large-scale benchmarks or datasets. Some recent efforts [9], [10], [11] have been devoted to construct datasets with drone platform focusing on object detection or tracking.

These datasets are still limited in size and scenarios covered, due to the difficulties in data collection and annotation. Thorough evaluations of existing or newly developed algorithms remain an open problem. Thus, a more general and comprehensive benchmark is desired for further boosting visual analysis research on drone platforms.

Thus motivated, we present a large scale benchmark, named **VisDrone2018**, with carefully annotated ground-truth for various important computer vision tasks, to make vision meets drones. The benchmark dataset consists of 263 video clips formed by $179, 264$ frames and $10, 209$ static images, captured by various drone-mounted cameras, diverse in a wide range of aspects including location (taken from 14 different cities in China), environment (urban and country), objects (pedestrian, vehicles, bicycles, *etc*.), and density (sparse and crowded scenes), *etc*. With thorough annotations of over 2.5 million object instances, the benchmark focuses on four tasks:

- **Task 1: object detection in images.** Given a predefined set of object classes (*e.g.*, cars and pedestrians), the task aims to detect objects of these classes from individual images taken from drones.
- **Task 2: object detection in videos.** The task is similar to **Task 1**, except that objects are detected from videos taken from drones.
- **Task 3: single object tracking.** The task aims to estimate the state of a target, indicated in the first frame, across frames in an online manner.
- **Task 4: multi-object tracking.** The task aims to recover the object trajectories with (**Task 4B**) or without (**Task 4A**) the detection results in each video frame.

In this challenge we select ten categories of objects of frequent interests in drone applications, such as pedestrians and cars. Altogether we carefully annotated more than 2.5 million bounding boxes of object instances from these categories. Moreover, some important attributes including visibility of scenes, object category and occlusion, are provided for better data usage. The detailed comparison of

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the provided drone datasets with other related benchmark datasets in object detection and tracking are presented in Table 1.

2 RELATED WORK

In recent years, the computer vision community has developed various benchmarks for numerous tasks, including generic object detection [3], [4], pedestrian detection [1], single object tracking [5], [24], multi-object tracking [7], [8], 3D reconstruction [28], and optical flow [2], [29], which are extremely helpful to advance the state of the art in the respective areas. In this section, we review the most relevant drone-based benchmarks and other benchmarks in object detection and tracking fields.

2.1 Drone-based Datasets

To date, there only exists a handful of drone-based datasets in computer vision field. Hsieh *et al.* [10] present a dataset for car counting, which consists of $1,448$ images captured in parking lot scenarios with the drone platform, including $89,777$ annotated cars. Robicquet *et al.* [11] collect several video sequences with the drone platform in campuses, including various types of objects, (*i.e.*, pedestrians, bikes, skateboarders, cars, buses, and golf carts), which enable the design of new object tracking and trajectory forecasting algorithms. Barekatain [21] present a new Okutama-Action dataset for concurrent human action detection with the aerial view. The dataset includes 43 minute-long fully-annotated sequences with 12 action classes. In [9], a high-resolution UAV123 dataset is presented for single object tracking, which contains 123 aerial video sequences with $110k$ ($1k = 1,000$) fully annotated frames, including the bounding boxes of people and their corresponding action labels. Li *et al.* [30] capture 70 video sequences of high diversity by drone cameras and manually annotate the bounding boxes of objects for single object tracking evaluation. In [31], Rozantsev *et al.*present two separate datasets for detecting flying objects, *i.e.*, the UAV dataset and the aircraft dataset. The former one comprises 20 video sequences with the resolution 752×480 and $8,000$ annotated bounding boxes of objects, acquired by a camera mounted on a drone flying indoors and outdoors. The latter one consists of 20 publicly available videos of radio-controlled planes with $4,000$ annotated bounding boxes. In contrast to the aforementioned datasets acquired in constrained scenarios for single object tracking or object detection and counting, our **VisDrone2018** dataset is captured in various unconstrained urban scenes, focusing on four core problems in computer vision fields, *i.e.*, object detection in images, object detection in videos, single object tracking, and multi-object tracking.

2.2 Object Detection Datasets

Several object detection benchmarks have been collected for evaluating object detection algorithms. Enzweiler and Gavrila [32] present the Daimler dataset, captured by a vehicle driving through urban environment. The dataset includes $3,915$ manually annotated pedestrians in video images in the training set, and $21,790$ video images with $56,492$ annotated pedestrians in the testing set. Caltech [1]

consists of approximately 10 hours of 640×480 30Hz videos taken from a vehicle driving through regular traffic in an urban environment. It contains $\sim 250,000$ frames with a total of $350,000$ annotated bounding boxes of $2,300$ unique pedestrians. KITTI-D [2] is designed to evaluate the car, pedestrian, and cyclist detection algorithms in autonomous driving scenarios, with $7,481$ training and $7,518$ testing images. Mundhenk *et al.* [19] create a large dataset for classification, detection and counting of cars, which contains $32,716$ unique cars from six different image sets, each covering a different geographical location and produced by different imagers. The recent UA-DETRAC benchmark [8], [33] provides $1,210k$ objects in $140k$ frames for vehicle detection.

The PASCAL VOC dataset [34], [35] is one of the pioneering work in generic object detection filed, which is designed to provide a standardized test bed for object detection, image classification, object segmentation, person layout, and action classification. ImageNet [3], [36] follows the footsteps of the PASCAL VOC dataset by scaling up more than an order of magnitude in number of object classes and images, *i.e.*, PASCAL VOC 2012 has 20 object classes and $21,738$ images *vs.* ILSVRC2012 with $1,000$ object classes and $1,431,167$ annotated images. Recently, Lin *et al.* [4] release the MS COCO dataset, containing more than $328,000$ images with 2.5 million manually segmented object instances. It has 91 object categories with $27k$ instances on average per category. Notably, it contains object segmentation annotations which are not available in ImageNet.

2.3 Object Tracking Datasets

Single-object tracking. Single object tracking is one of the fundamental problems in computer vision, which aims to estimate the trajectory of a target in a video sequence, with its given initial state. In recent years, numerous datasets have been developed for single object tracking evaluation. Wu *et al.* [37] develop a standard platform to evaluate the single object tracking algorithms, and scale up the data size from 50 sequences to 100 sequences in [5]. Similarly, Liang *et al.* [23] collect 128 video sequences for evaluating the color enhanced trackers. To track the progress in visual tracking field, Kristan *et al.* [24], [38], [39] organize a VOT competition from 2013 to 2017 by presenting new datasets and evaluation strategies for tracking evaluation. Smeulders *et al.* [22] present the ALOV300 dataset, which contains 314 video sequences with 14 visual attributes, such as long duration, zooming camera, moving camera and transparency. Li *et al.* [40] construct a large-scale dataset with 365 video sequences of pedestrians and rigid objects, covering 12 kinds of objects captured from moving cameras. Du *et al.* [41] design a dataset including 50 annotated video sequences, focusing on deformable object tracking in unconstrained environments. To evaluate tracking algorithms in higher frame rate video sequences, Galoogahi *et al.* [25] propose a dataset including 100 videos ($380k$ frames) recorded by the higher frame rate cameras (240 frame per second) from real world scenarios. Besides using video sequences captured by RGB cameras, Felsberg *et al.* [42], [43] organize a series of competitions from 2015 to 2017, focusing on visual tracking on thermal video sequences recorded by eight different types of sensors. In [44], a RGB-D tracking dataset is presented, which

TABLE 1: Comparison of Current State-of-the-Art Benchmarks and Datasets. Note that, the resolution indicates the maximum resolution of the videos/images included in the dataset.

Object detection in images	scenario	#images	categories	avg. #labels/categories	resolution	occlusion labels	year
UIUC [12]	life	1,378	1	739	200×150		2004
INRIA [13]	life	2,273	1	1,774	96×160		2005
ETHZ Pedestrian [14]	life	2,293	1	10.9k	640×480		2007
TUD [15]	life	1,818	1	3,274	640×480		2008
EPFL Multi-View Car [16]	exhibition	2,000	1	2,000	376×250		2009
Caltech Pedestrian [1]	driving	249k	1	347k	640×480	√	2012
KITTI Detection [2]	driving	15.4k	2	80k	1241×376	√	2012
PASCAL VOC2012 [17]	life	22.5k	20	1,373	469×387	√	2012
ImageNet Object Detection [3]	life	456.2k	200	2,007	482×415	√	2013
MS COCO [4]	life	328.0k	91	27.5k	640×640		2014
VEDAI [18]	satellite	1.2k	9	733	1024×1024		2015
COWC [19]	aerial	32.7k	1	32.7k	2048×2048		2016
CARPK [10]	drone	1,448	1	89.8k	1280×720		2017
VisDrone2018	drone	10,209	10	54.2k	2000×1500	√	2018

Object detection in videos	scenario	#frames	categories	avg. #labels/categories	resolution	occlusion labels	year
ImageNet Video Detection [3]	life	2017.6k	30	66.8k	1280×1080	√	2015
UA-DETRAC Detection [8]	surveillance	140.1k	4	302.5k	960×540	√	2015
MOT17Det [20]	life	11.2k	1	392.8k	1920×1080	√	2017
Okutama-Action [21]	drone	77.4k	1	422.1k	3840×2160		2017
VisDrone2018	drone	40.0k	10	183.3k	3840×2160	√	2018

Single object tracking	scenarios	#sequences	#frames	year
ALOV3000 [22]	life	314	151.6k	2014
OTB100 [5]	life	100	59.0k	2015
TC128 [23]	life	128	55.3k	2015
VOT2016 [24]	life	60	21.5k	2016
UAV123 [9]	drone	123	110k	2016
NfS [25]	life	100	383k	2017
POT 210 [26]	planar objects	210	105.2k	2018
VisDrone2018	drone	167	139.3k	2018

Multi-object tracking	scenario	#frames	categories	avg. #labels/categories	resolution	occlusion labels	year
KITTI Tracking [2]	driving	19.1k	5	19.0k	1392×512	√	2013
MOTChallenge 2015 [7]	surveillance	11.3k	1	101.3k	1920×1080		2015
UA-DETRAC Tracking [8]	surveillance	140.1k	4	302.5k	960×540	√	2015
DukeMTMC [27]	surveillance	2852.2k	1	4077.1k	1920×1080		2016
Campus [11]	drone	929.5k	6	1769.4k	1417×2019		2016
MOT17 [20]	surveillance	11.2k	1	392.8k	1920×1080		2017
VisDrone2018	drone	40.0k	10	183.3k	3840×2160	√	2018

includes 100 video clips with RGB and depth channels and manually annotated ground truth bounding boxes.

Multi-object tracking. Multi-object tracking is another important research problem with many applications, such as surveillance, behavior analysis, and autonomous driving. Some of the most widely used multi-object tracking evaluation datasets include the PETS09 [45], PETS16 [46], KITTI-T [2], MOTChallenge [7], [47], and UA-DETRAC [8], [33]. Specifically, the PETS09 [45] and PETS16 [46] datasets mainly focus on multi-pedestrian detection, tracking and counting in the surveillance scenarios. KITTI-T [2] is designed for object tracking in autonomous driving, which is recorded from a moving vehicle with viewpoint of the driver. MOT15 [7] and MOT16 [47] aim to provide a unified dataset, platform, and evaluation protocol for multiple object tracking algorithms, including 22 and 14 sequences respectively. Recently, the UA-DETRAC benchmark [8], [33] is constructed, which contains a total of 100 sequences to track multiple vehicles, where sequences are filmed from a surveillance viewpoint.

Moreover, in some scenarios, a network of cameras are set up to capture multi-view information to help multi-object tracking. The datasets in [45], [48] are recorded using multi-camera with fully overlapping views in constrained environments. Other datasets are captured by non-overlapping cameras. For example, Chen *et al.* [49] collect four datasets, each of which includes 3 to 5 cameras with non-overlapping views in real scenes and simulation environments. In [50], the dataset is captured by 3 cameras in the campus environments with the resolution of 852×480 and 25 minutes length. Zhang *et al.* [51] develop a dataset composed of 5 to 8 cameras covering both indoor and outdoor scenes at a university. Ristani *et al.* [27] organize a challenge and present a large-scale fully-annotated and calibrated dataset, including more than 2 million 1080p video frames taken by 8 cameras with more than 2,700 identities.

3 VISDRONE2018 BENCHMARK DATASET

3.1 Dataset Collection

A critical basis for effective algorithm evaluation is a thorough dataset. For this purpose, in **VisDrone2018**, we sys-
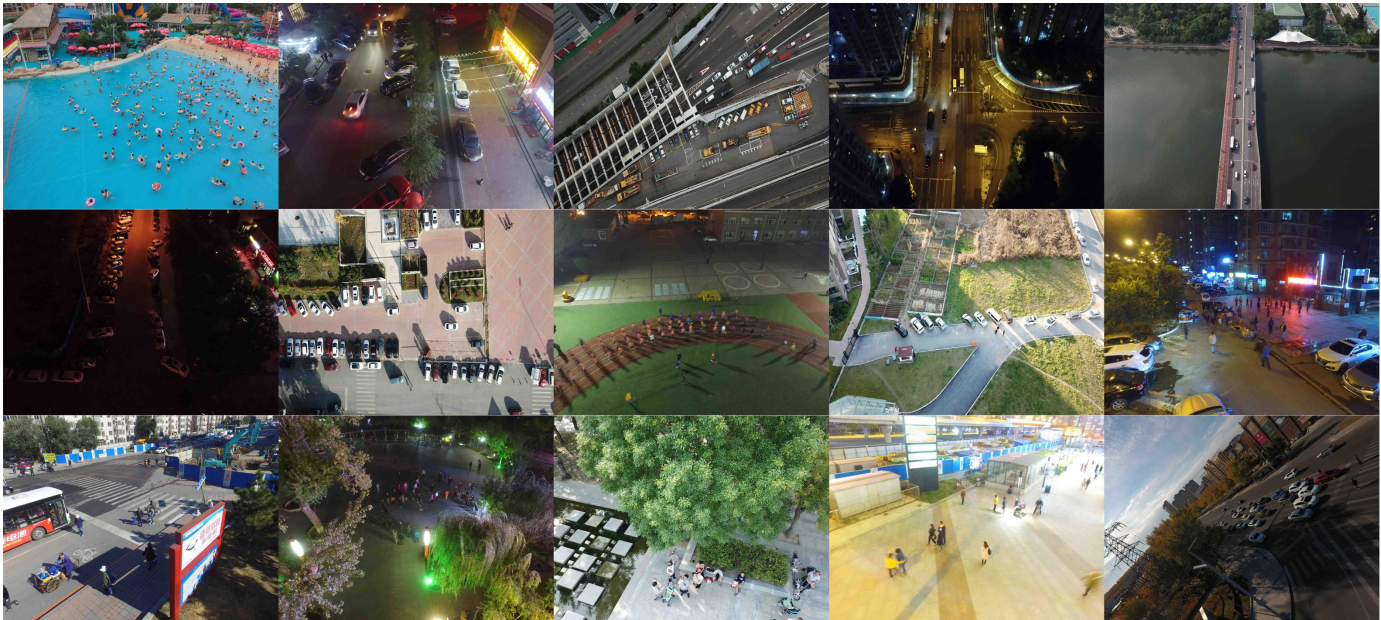
Fig. 1: Some example static images for **Task 1** (object detection in images) in the **VisDrone2018** challenge.

Fig. 2: Some example screenshots of video clips for **Task 2** (object detection in videos), **Task 3** (single object tracking), and **Task 4** (multi-object tracking) in the **VisDrone2018** challenge. The frame index is placed on the left top corner of each screenshot.

tematically collected the largest, to the best of our knowledge, drone image/video dataset. Our dataset consists of 263 video clips with 179, 264 frames and additional 10, 209 static images. The videos/images are acquired by various drone platforms, *i.e.*, DJI Mavic, Phantom series (3, 3A, 3SE, 3P, 4, 4A, 4P), including different scenarios across 14 different cites in China, *i.e.*, Tianjin, Hongkong, Daqing, Ganzhou, Guangzhou, Jincang, Liuzhou, Nanjing, Shaoxing, Shenyang, Nanyang, Zhangjiakou, Suzhou and Xuzhou. The dataset covers various weather and lighting conditions, representing diverse scenarios in our daily life. The maximal resolutions of video clips and static images are 3840×2160 and 2000×1500, respectively. Some example images and video clips are shown in Figures 1 and 2.

A website: www.aiskyeye.com is constructed for access-

ing the **VisDrone2018** benchmark and perform evaluation of the four tasks, *i.e.*, (1) object detection in images, (2) object detection in videos, (3) single object tracking, and (4) multi-object tracking. Specifically, a user is required to create an account using an institutional email address. After registration, the user can choose the tasks which she or he decides to participate, and submit the results using the corresponding account. Notably, for each task, the images/videos in the training, validation, and testing sets are captured at different locations, but with similar scenarios. The manually annotated ground truths for training and validation are made available to users, but the ground truths of the testing set are reserved in order to avoid (over)fitting of algorithms. We encourage the participants to use the provided training data, but also allow them to use additional training data.

Fig. 3: Some annotated example images of (**Task 1**) object detection in images. The dashed bounding box indicates the object is occluded. Different bounding box colors indicate different classes of objects. For better visualization, we only display some attributes.

The use of additional training data must be indicated during submission. In the following subsections, we describe each task and the corresponding data annotation and statistics in details.

3.2 Task 1: Object Detection in Images

Given an input image and a predefined set of object categories, *e.g.*, car and pedestrian, the task of object detection (in images) aims to locate all the object instances in these categories from the image (if any). Typically and in our benchmark, for each object class, we require a detection algorithm to predict the bounding box of each instance of that class in the image, with a real-valued confidence. The **VisDrone2018** provides a dataset of $10,209$ images for this task, with $6,471$ images used for training, 548 for validation and $3,190$ for testing. The images of the three subsets are taken at different locations, but share similar environments and attributes. We plot the number of objects per image *vs.* percentage of images in each subset to show the distributions of the number of objects in each image of the training, validation and testing sets in Figure 5.

For object categories, we mainly focus on human and vehicles in our daily life, and define ten object categories of interest including *pedestrian*, *person*[1], *car*, *van*, *bus*, *truck*, *motor*, *bicycle*, *awning-tricycle*, and *tricycle*. Some rarely occurring special vehicles (*e.g.*, machineshop truck, forklift truck, and tanker) are ignored in evaluation. We manually annotate the bounding boxes of different categories of objects in each image. In addition, we also provide two kinds of useful annotations, occlusion ratio and truncation ratio. Specifically, we use the fraction of objects being occluded to

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1. If a human maintains standing pose or walking, we classify it as *pedestrian*; otherwise, it is classified as a *person*.

define the occlusion ratio, and define three degrees of occlusions: no occlusion (occlusion ratio 0%), partial occlusion (occlusion ratio $1\% \sim 50\%$), and heavy occlusion (occlusion ratio $> 50\%$). For truncation ratio, it is used to indicate the degree of object parts appears outside a frame. If an object is not fully captured within a frame, we annotate the bounding box across the frame boundary and estimate the truncation ratio based on the region outside the image. It is worth mentioning that a target is skipped during evaluation if its truncation ratio is larger than 50%. We show some annotated examples in Figure 3, and present the number of objects with different occlusion degrees of different object categories in the training, validation, and testing sets in Figure 6.

3.2.1 Evaluation Criteria

We require each evaluated algorithm in **Task 1** (object detection in images) to output a list of detected bounding boxes with confidence scores for each test image. Following the evaluation protocol in MS COCO [4], we use the $\mathrm{AP}^{\mathrm{IoU}=0.50:0.05:0.95}$, $\mathrm{AP}^{\mathrm{IoU}=0.50}$, $\mathrm{AP}^{\mathrm{IoU}=0.75}$, $\mathrm{AR}^{\max=1}$, $\mathrm{AR}^{\max=10}$, $\mathrm{AR}^{\max=100}$ and $\mathrm{AR}^{\max=500}$ metrics to evaluate the results of detection algorithms. These criteria penalize missing detection of objects as well as duplicate detections (two detection results for the same object instance). Specifically, $\mathrm{AP}^{\mathrm{IoU}=0.50:0.05:0.95}$ is computed by averaging over all 10 intersection over union (IoU) thresholds (*i.e.*, in the range $[0.50 : 0.95]$ with the uniform step size 0.05) of all categories, which is used as the primary metric for ranking. $\mathrm{AP}^{\mathrm{IoU}=0.50}$ and $\mathrm{AP}^{\mathrm{IoU}=0.75}$ are computed at the single IoU thresholds 0.5 and 0.75 over all categories, respectively. The $\mathrm{AR}^{\max=1}$, $\mathrm{AR}^{\max=10}$, and $\mathrm{AR}^{\max=100}$ scores are the maximum recalls given 1, 10, 100 and 500 detections per image, averaged
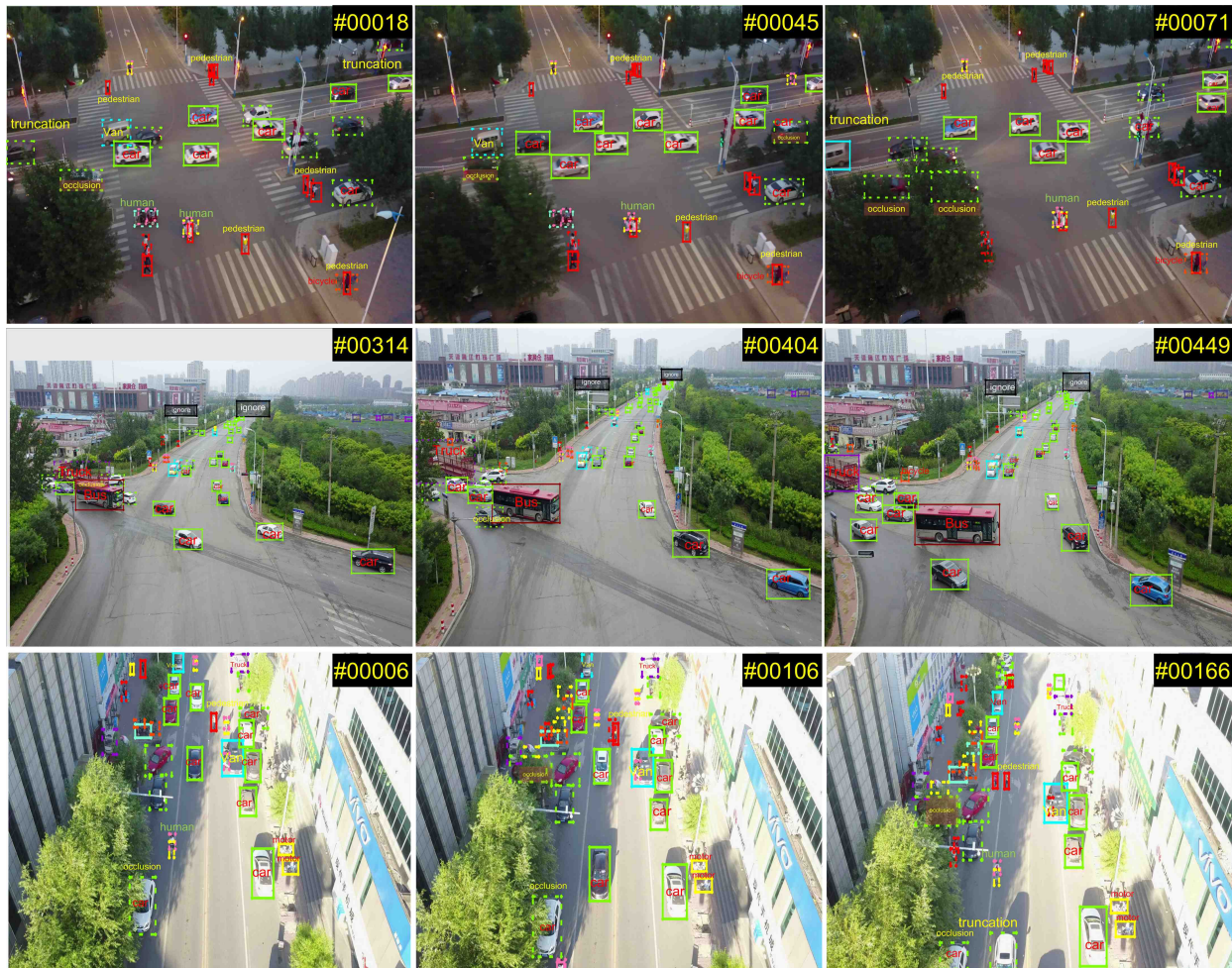
Fig. 4: Some annotated example video frames of (**Task 2**) object detection in videos. The dashed bounding box indicates the object is occluded. Different bounding box colors indicate different classes of objects. For better visualization, we only display some attributes.

over all categories and IoU thresholds. Please refer to [4] for more details.

3.3 Task 2: Object Detection in Videos

Similar to **Task 1**, the task of object detection in videos aims to locate object instances from a predefined set of categories, but the detection is from a *video* instead of a static image as in **Task 1**. Specifically, given a video clip, a detection algorithm is required to produce a set of bounding boxes of each object instance in each video frame (if any), with real-valued confidences. We provide 96 challenging video clips for the task, including 56 clips for training (24, 201 frames in total), 7 for validation (2, 819 frames in total) and 33 for testing (12, 968 frames in total). The videos of the three subsets are recorded at different locations, but share similar environments and attributes. We plot the number of objects per frame *vs.* percentage of frames for training, validation, and testing sets in Figure 8.

We use the same object categories as that in (**Task 1**) and provide manually annotated ground truth bounding boxes in each video frame. Similar to (**Task 1**), we also provide the annotations of occlusion and truncation ratios of each object. We show some annotated examples in Figure 4, and present

the number of objects with different occlusion degrees of different object categories in training, validation, and testing sets in Figure 9.

3.3.1 Evaluation Criteria

For **Task 2**, we require each evaluated algorithm to generate a list of bounding box detections with confidences in each video frame. Motivated by the evaluation protocols in MS COCO [4] and ILSVRC [52], we use the $AP^{IoU=0.50:0.05:0.95}$, $AP^{IoU=0.50}$, $AP^{IoU=0.75}$, $AR^{max=1}$, $AR^{max=10}$, $AR^{max=100}$ and $AR^{max=500}$ metrics to evaluate the results of detection algorithms, which is similar to **Task 1**. Notably, the $AP^{IoU=0.50:0.05:0.95}$ score is used as the primary metric for ranking methods. Please see [4], [52] for more details.

3.4 Task 3: Single Object Tracking

While the term "object tracking" can be sometimes ambiguous, in **Task 3** we focus on generic single object tracking, also known as model-free tracking. In particular, for an input video sequence and the initial bounding box of the target object in the first frame, **Task 3** requires a tracking algorithm to locate the target bounding boxes in the subsequent video frames. We provide 167 video sequences with manually
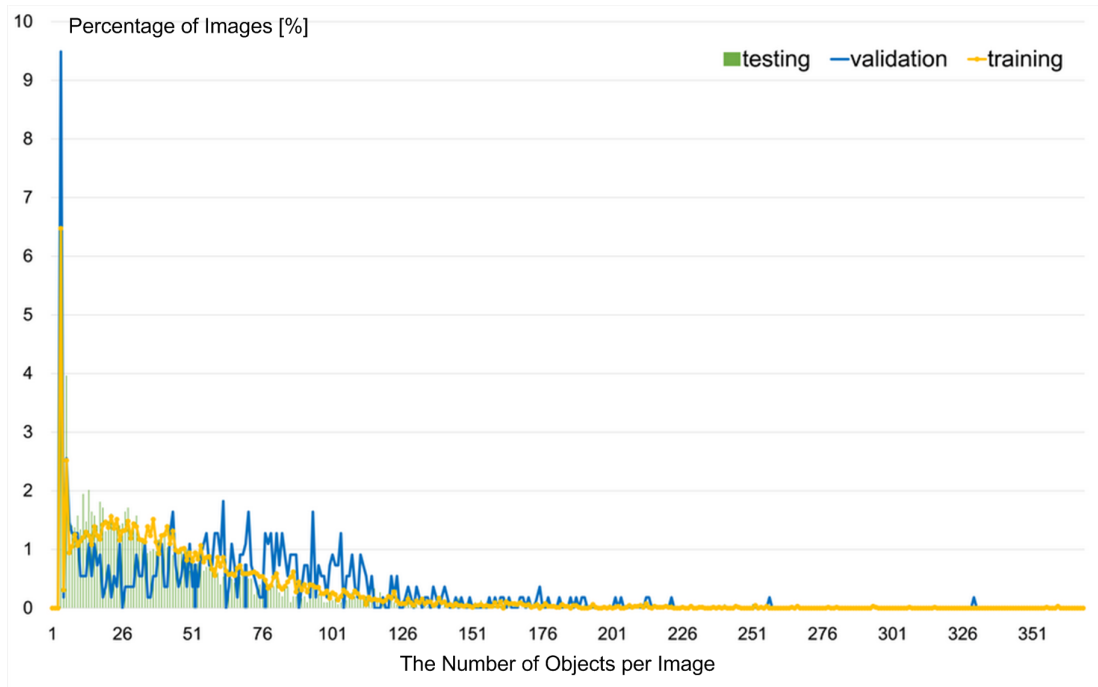
Fig. 5: The number of objects per image *vs.* percentage of images in the training, validation and testing sets for (**Task 1**) object detection in images.
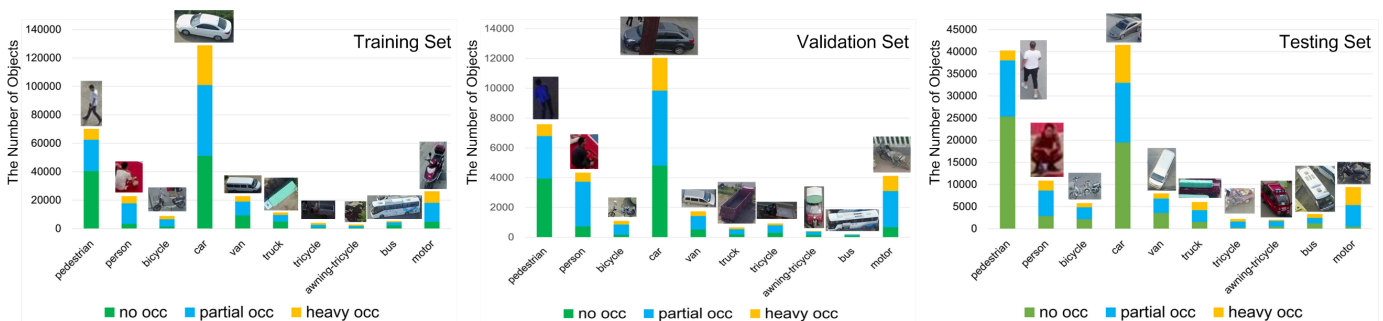

Fig. 6: The number of objects with different occlusion degrees of different object categories in the training, validation and testing sets for (**Task 1**) object detection in images.

annotated target ground truths. Unlike most previous single object tracking benchmarks, we divide all these video clips into training, validation, and testing sets, with 86 sequences (69, 941 frames in total), 11 sequences (7, 046 frames in total) and 70 sequences (62, 289 frames in total), respectively. The tracking targets in these sequences include pedestrians, cars, buses, and animals. Some annotated examples and the statistics of targets are presented in Figure 7 and 10.

3.4.1 Evaluation Criteria

For the single object tracking task, the performance is evaluated by the success and precision scores, same as in [5]. Specifically, we plot the percentage of successfully tracked frames *vs.* the bounding box overlap threshold, and use the area under the curve (AUC) as the evaluation criterion. Meanwhile, we also plot the percentage curve of frames where the centers of the tracked object are within the given threshold distance to the ground truth, and use the percentage at the threshold of 20 pixels as the precision score in

evaluation. Notably, the success score is used as the primary metric for ranking methods.

3.5 Task 4: Multi-Object Tracking

Given an input video sequence, multi-object tracking aims to recover the trajectories of objects in the video. The task uses the same data as in **Task 2** (*i.e.*, object detection in videos). Depends on the availability of prior object detection results, **Task 4** is divided into two sub-tasks, denoted by **Task 4A** (without prior detection) and **Task 4B** (with prior detection). Specifically, for **Task 4A**, an evaluated algorithm is required to recover the trajectories of objects in video sequences without taking the object detection results as input. By contrast, for **Task 4B**, prior object detection results are provided and an evaluated algorithm can work on top of the prior detection. The number of objects *vs.* percentage of frames in training, validation, and testing sets are plotted in Figure 8; some annotated examples are given in Figure 11; and the number of objects with different occlusion degrees
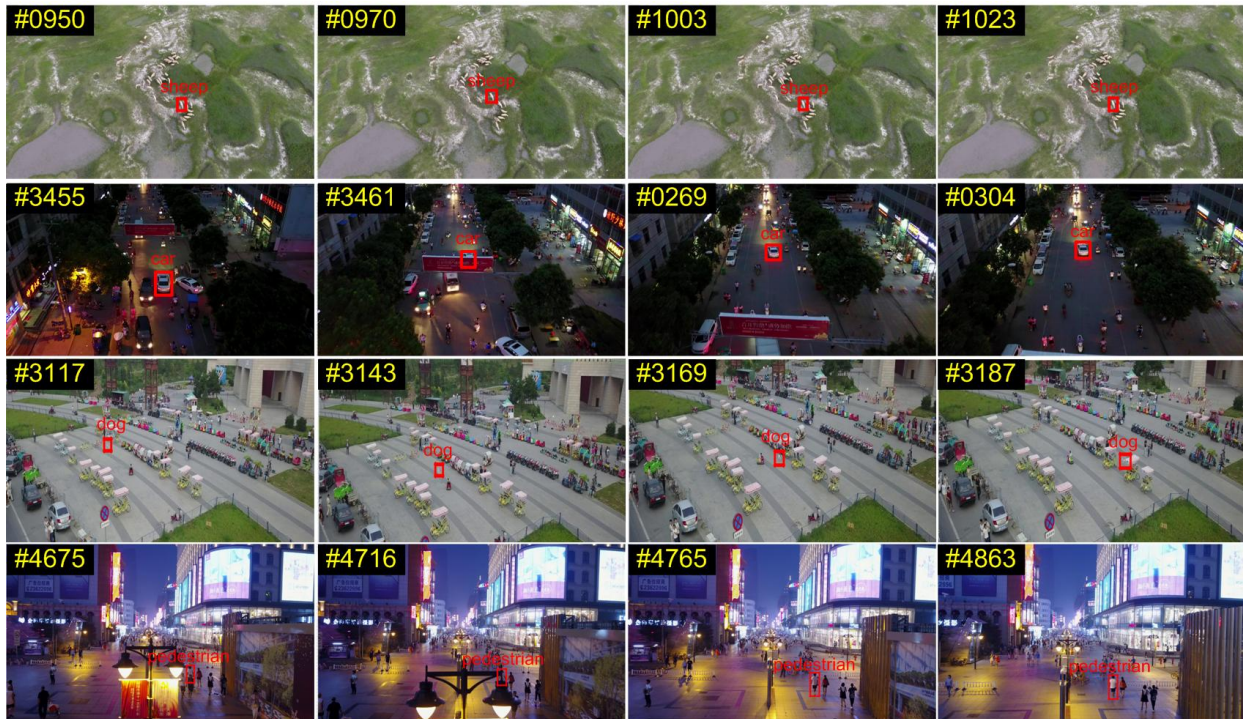
Fig. 7: Some annotated example video frames of (**Task 3**) single object tracking.

of different object categories in training, validation, and testing sets are presented in Figure 9.

3.5.1 Evaluation Criteria

For **Task 4A**, we use the protocol in [52] to evaluate the tracking performance. Specifically, each algorithm is required to output a list of bounding boxes with confidence scores and the corresponding identities. We sort the tracklets (formed by the bounding box detections with the same identity) according to the average confidence of their bounding box detections. A tracklet is considered correct if the intersection over union (IoU) overlap with ground truth tracklet is larger than a threshold. Similar to [52], we use three thresholds in evaluation, *i.e.*, 0.25, 0.50, and 0.75. The performance of an algorithm is evaluated by averaging the mean average precision (mAP) per object class over different thresholds. Please refer to [52] for more details.

For **Task 4B**, we use the protocol in [53] to evaluate the algorithm performance. More specifically, the average rank of 10 metrics (*i.e.*, MOTA, IDF1, FAF, MT, ML, FP, FN, IDS, FM, and Hz) is used to compare different algorithms. The MOTA metric combines three error sources: FP, FN and IDS. The IDF1 metric indicates the ratio of correctly identified detections over the average number of ground truth and computed detections. The FAF metric indicates the average number of false alarms per frame. The FP metric describes the total number of tracker outputs which are the false alarms, and FN is the total number of targets missed by any tracked trajectories in each frame. The IDS metric describes the total number of times that the matched identity of a tracked trajectory changes, while FM is the total number of times that trajectories are disconnected. Both the IDS and FM metrics reflect the accuracy of tracked trajectories. The ML and MT metrics measure the percentage of tracked trajectories less than 20% and more than 80% of the time span based on the ground truth respectively. The Hz metric indicates the processing speed of the algorithm.

4 CONCLUSION

We introduce a new large-scale benchmark, **VisDrone2018**, to facilitate the research of object detection and tracking on the drone platform. With over $6,000$ worker hours, a vast collection of object instances are gathered, annotated, and organized to drive the advancement of object detection and tracking algorithms. We place emphasis on capturing images and video clips in real life environments. Notably, the dataset is recorded over 14 different cites in China with various drone platforms, featuring a diverse real-world scenarios. We provide a rich set of annotations including more than 2.5 million annotated object instances along with several important attributes. The **VisDrone2018** benchmark is made available to the research community through the project website: www.aiskyeye.com. We expect the benchmark to largely boost the research and development in visual analysis on drone platforms.

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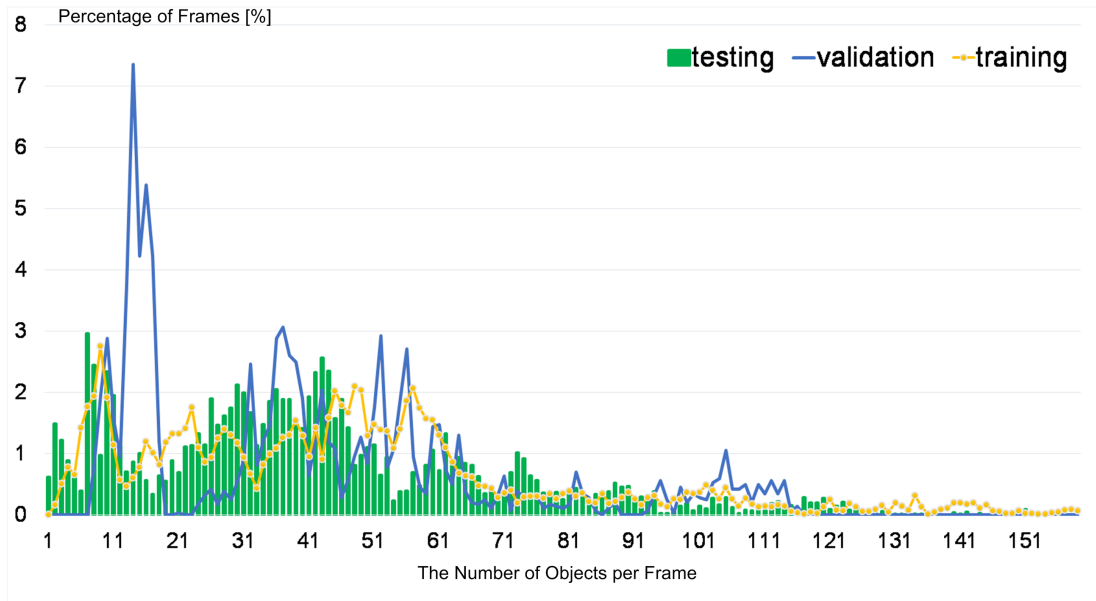
Fig. 8: The number of objects per frame *vs.* percentage of frames in the training, validation and testing sets for (**Task 2**) object detection in videos.
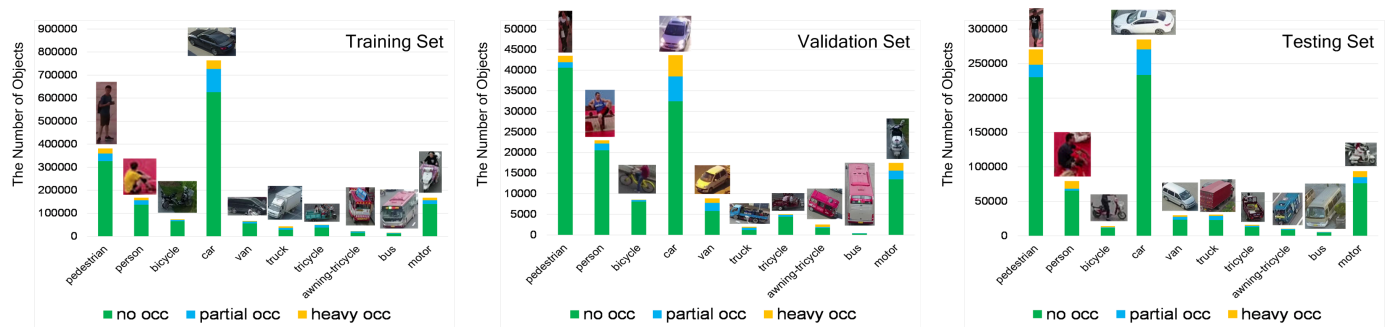

Fig. 9: The number of objects with different occlusion degrees of different object categories in the training, validation and testing sets for (**Task 2**) object detection in videos.

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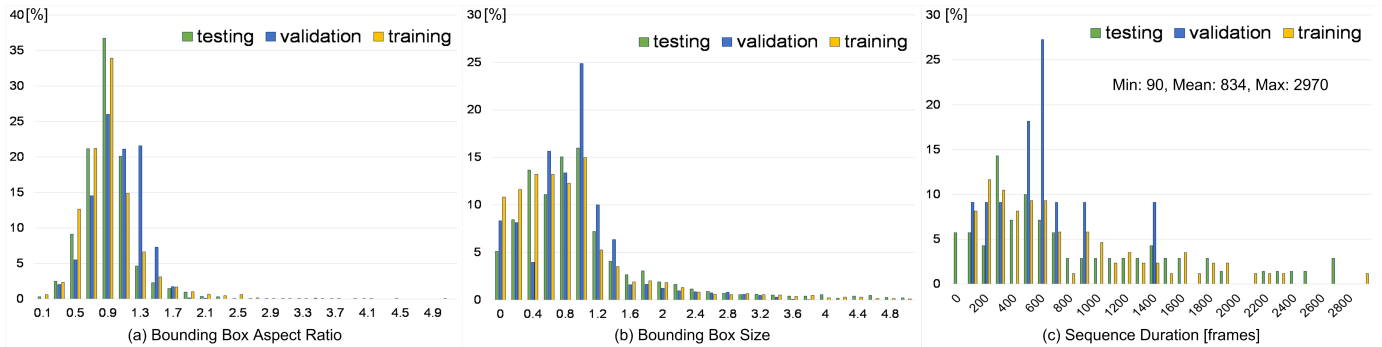
Fig. 10: (a) The number of frames *vs.* the aspect ratio (height divided by width) change rate with respect to the first frame, (b) the number of frames *vs.* the area change rate with respect to the first frame, and (c) the distributions of the number of frames of video clips, in the training, validation and testing sets for (**Task 3**) single object tracking.

Fig. 11: Some annotated example video frames of (**Task 4**) multi-object tracking. The dashed bounding box indicates the object is occluded. Different bounding box colors indicate different classes of objects. The identities of the objects are shown at the left corner of the bounding boxes. For better visualization, we only display some identities of the targets and attributes.

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