IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 16 August 2022, accepted 27 August 2022, date of publication 31 August 2022, date of current version 9 September 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3203188

APPLIED RESEARCH

The JKU DORA Traffic Dataset

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ABSTRACT Development and testing of Advanced Driver Assistance Systems (ADAS) is largely based on models and simulations, but real data are indispensable for many reasons – to determine the relevant scenarios, to establish a connection between the results of the simulations and the real situation and of course as elements to set up realistic models. Using data, however, is not trivial, as not all data are informative, and even extensive data sets are often incomplete. Indeed, data is not automatically information, and the richness of the data sets is more important than their size. Data should be diverse not only with respect to different scenarios but also geographically in order to be not biased towards a specific location. In this paper, we present a new aerial-view dataset ''Drone Over Roads'' (DORA) of highway exits and entrances. The data have been collected by the Johannes Kepler University Linz (JKU), Austria and Italy and contain positions, velocities, and accelerations (in both local and global coordinate systems) of cars, vans, and trucks for Austria and additionally for motorbikes and buses in Italy. The uniqueness of the dataset consists not only in the measurements in different countries, but also in the flight height in Austria, where the recordings have been taken from 300 meters altitude allowing to observe an over 600 meters long section of the road. For non-commercial use, the dataset is available free of charge at the IEEE DataPort.

INDEX TERMS Dataset, drone data, highway entrances/exits, traffic.

I. INTRODUCTION

Datasets are crucial for developing perception systems for assisted and autonomous driving as their processing can lead to conclusions that can be used as a reference to improve existing systems and validate future approaches. In the last decade, research on Intelligent Transportation Systems (ITS) has relied on datasets available from various sources: open, such as Kaggle [1], and with limited access or closed, such as the ones collected by research institutions and companies. However, these data are not always appropriate for investigating all on-road situations. Although the usefulness of varying data collections has been demonstrated, a larger amount of training data is needed to address the needs arising from current learning and prediction architectures. In addition, diversification of data is required that pertain to different geographical locations and environmental conditions. This data diversification will ensure proximity to the real world.

The associate editor coordinating the review of this manuscript and approving it for publication was Chong Leong Gan.

The available datasets may be divided into four categories, each with its own set of features and applications, as explained below.

A. DATA FROM TEST VEHICLES

A vehicle geared up with cameras, LIght Detection And Ranging (LIDAR) sensors, Global Positioning System (GPS), and Inertial Measurement Unit (IMU) is set to record data while traversing different locations in a naturalistic way. The dataset from a project of Karlsruhe Institute of Technology and Toyota Technological Institute at Chicago (KITTI) [2] is arguably one of the most used so far, comprising images and LIDAR scans that are acquired from a sensor suit located over the rooftop of a vehicle. Over the last years several research institutions, AI companies, and car makers such as Berkeley [3], Waymo [4], [5], Ford [6] and Audi [7] have been recording their own datasets and releasing them to the public. Some of these datasets are fully annotated with location, speed, acceleration, size, and type of each one of the agents present in the recordings or just the segmentation information at pixel level.

B. DATA FROM FIXED STATIONS

In this case, the data are acquired by a sensor arrangement located on street-light poles, custom poles, or by the side of buildings pointing to public intersections or zones of interest. The use of a fixed location has the benefit of having power lines in place that allow long recordings. In addition, there is no need to track the sensor arrangement location with additional sensors, and finally, the fixed background represents an advantage for perception algorithms. However, these advantages also come with certain drawbacks. Since the angle of view is oblique to the road surface, there will be occlusions between the agents and also due to the surrounding buildings. Furthermore, the possible interactions are limited to a specific area.

The Next Generation Simulation (NGSIM) [8] is probably the largest dataset of this type so far. The NGSIM program collected high-quality traffic videos at four different locations in the US, including two freeway segments and two arterial segments, between 2005 and 2006. A less ambitious project, the Ko-PER intersection dataset [9], depicted data from cameras and laser scanners as well as reference data and object labels generated in a single public intersection. In another example, the Urban Tracker project [10] recorded a dataset from fixed cameras at several different locations ranging from a couple of meters above the floor to several floors by the side of a building.

C. DATA FROM API

With the help of an Application Programming Interface (API), providers as for example HERE [11], Google [12] or TomTom [13] make information about current traffic conditions on a route available for use. While Google only returns the congestion level on a route through coloring a map, the TomTom API returns current travel time and traffic flow as well as historical data such as speeds, etc. The HERE API even returns, among others, real-time traffic information and traffic prediction on a requested route. The information of HERE has been used for instance in [14] to develop a long-term prediction method of macroscopic velocities that can be used, e.g., for hybrid powertrain energy management.

D. DATA FROM DRONES

With the development of cheaper and more reliable drones, some institutions started to use them to record data from a bird's point of view. This point of view that is (almost) perpendicular to the road allows to avoid the occlusions caused by using an oblique or parallel view as in the previous types of datasets. As a drawback, there is a limitation in the recording time due to the battery of the drone and also the number of sensors is limited by the drone's payload. One of the first large-scale datasets of this type was the Stanford Drone Dataset [15]. It consists of aerial videos (bird's view) from multiple classes of targets interacting in complex outdoor spaces around the Stanford University campus. This dataset took into account pedestrians, bikers, skaters, cars, and carts, all interacting between them. A more recent example is the Semantic Drone Dataset [16] that focuses on semantic understanding of urban scenes acquired at an altitude of 5 to 30 meters above ground level.

The German company fka GmbH from Aachen has published several high-quality drone datasets of different scenarios in Germany [17]. They recorded not only highways [18], [19], but city scenarios [20], [21] as well.

To contribute to the body of research we present in this paper a collection of data that has been further processed to be used in perception algorithms. The data were collected using two different drones that were equipped with the necessary navigation gear and a camera. We make this dataset available to the scientific community to facilitate a common basis for the development of ITS applications.

Our dataset, called DORA (**D**rone **O**ver **R**o**a**ds), has been filmed in two different countries (Austria and Italy) from an extraordinary (300 m) height in Austria, allowing a bigger scene to be captured, and from a 120 m height in Italy. The main focus has been put on highway entrances; however, the dataset includes exits as well. Following the requirement formulated by [20], the DORA dataset

- Reflects the naturalistic behavior of road users
- Has a sufficient size of over 5000 trajectories.
- Has been collected at different locations and times.
- Detects and tracks different types of road users.
- Has a high accuracy.
- Includes the infrastructure.

II. PROPERTY AND LOCATION OF JKU DORA DATA

The acquisition of traffic data with the drone has been performed at different locations in Austria, near Linz, as well as in Italy, near Naples. The filming occurred at different times during daylight hours as well as good weather and wind conditions. The majority of the recorded videos show highway scenarios including overtaking and merging maneuvers, while the remaining videos show scenarios on country roads. In the following part of this section, details about the Austrian and Italian videos are given, whereas in the next section, information about already post-processed data including resolution, statistical information, and the processing toolchain is provided.

A. VIDEOS RECORDED IN AUSTRIA

In total, 36 hours of video material have been recorded at 9 different locations in Austria with a class C/III drone that is further specified in Section III-C1. The drone was flying at a height of 150 m for 23 hours of video material, whereas for the remaining 13 hours the drone was flying at a height of 300 m, thus, covering a travel distance of the filmed vehicles of approximately 620 m. Two of the nine locations show traffic scenarios on a country road (CR), whereas seven of the locations are highways (HW) (four of them with a merging ramp (HWmr) and three of them without a merging ramp (HW)). An example location can be seen in Fig. 1. Table 1 gives further details about the filmed videos for the Austrian dataset.

FIGURE 1. Recorded road section from Austria with corresponding laneIDs.

TABLE 1. Recorded videos for the Austrian dataset.

location	coordinates [lat,lon]	duration [h]	flight height [m]
CR1	48.336528, 14.384056	6.5	150
CR2	48.310885, 14.255639	0.5	300
HW1	48.336517, 14.331865	1	150
HW2	48.128962, 15.008882	1.5	150
HW3	48.186988, 14.534306	1	300
HWmr1	48.341701, 14.446443	14	150
HWmr2	48.334438, 14.360505	0.5	150
HWmr3	48.341701, 14.446443	6	300
HWmr4	48.191029, 14.528482	5	300

B. VIDEOS RECORDED IN ITALY

In Italy, in total 8 hours of video material have been recorded with the DJI Mini2 (see Section III-C1) at four different locations near Naples. The recorded videos show around 220 m long scenarios on highways, all of them including a merging ramp. An example location can be seen in Figure 2. Detailed information for the Italian videos can be seen in Table 2.

TABLE 2. Recorded videos for the Italian DORA dataset.

location	coordinates [lat,lon]	duration [h]	flight height [m]
HWmr1	40.883363, 14.090517	2.5	120
HWmr2	40.946263, 14.030297	2	120
HWmr3	41.081654, 14.853909	2.5	120
HWmr4	41.070200, 14.925314	1	120

III. JKU DORA DATASET

A. PROCESSED FILES

Recordings of two locations have been post-processed: in Austria at the A7 highway near Engerwitzberg, see Figure 1, and the road Via Domiziana, Giugliano in Campania NA in Italy, see Figure 2.

In Austria, the flights were performed at a 300 m above ground level and 40 m shifted aside the highway, so that about 620 m of the highway were recorded. Each flight took around 12 minutes and in total 8 flights have been post-processed. The resulting resolution is about 0.15 m and 24 Hz sample rate.

In Italy, the drone hovered 120 m above ground level at 120 m distance to the highway. Here about 220 m of the highway could be seen, with about 0.1 m per pixel resolution. The sampling rate here is 30 Hz.

Concerning object classes, cars, vans, and trucks have been distinguished for both locations, but for Italy motorbikes and buses were recognized additionally because of their frequent appearance in the data. The classification accuracy was estimated at around 95 %. In addition to the data provided in. csv format, the dataset is complemented by a specifically developed GUI for data visualization.

B. STATISTICAL PROPERTIES

1) AUSTRIAN DORA DATASET

The post-processed Austrian dataset contains 2521 vehicles. 1947 (77.2 %) of them are cars, 150 (6.0 %) are vans and 424 (16.8 %) vehicles belong to the class of trucks. Cars and vans are driving at a speed of 32.1 m/s and 35.1 m/s on average, respectively, whereas trucks are traveling more slowly at a speed of 23.4 m/s on average. The distribution of vehicles and their mean speeds can be seen in Figure 3. 56.7 % of the vehicles are driving on the same lane as long as they are visible in the video, which means that the remaining 43.3 % of the vehicles perform a maneuver. These maneuvers are either merging onto the highway (261 vehicles), exiting the highway (294 vehicles), or overtaking another vehicle (537).

2) ITALIAN DORA DATASET

The post-processed Italian dataset corresponds to location HWmr1 from Table 2 and consists of 2783 vehicles. In contrast to the Austrian dataset, the vehicles are further separated into motorcycles and buses. The corresponding amount of vehicles per type can be seen in Table 3, as well as the average speed of each vehicle class. The distribution of the average speed of each vehicle class can be seen in Figure 4. For the sake of clarity, buses and motorcycles are not included in Figure 4. In contrast to the Austrian part of the DORA dataset,

FIGURE 2. Recorded road section from Italy.

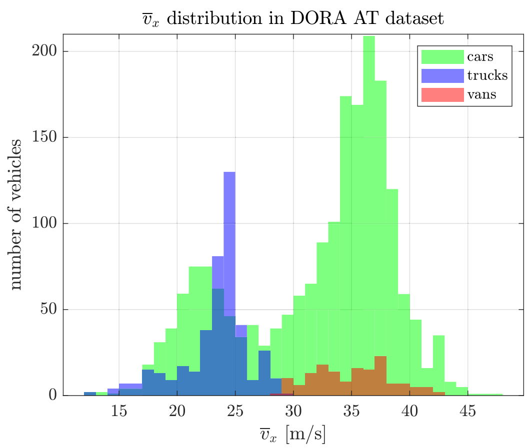

FIGURE 3. Distribution of the traffic participants' mean velocities in the Austrian part of the DORA dataset.

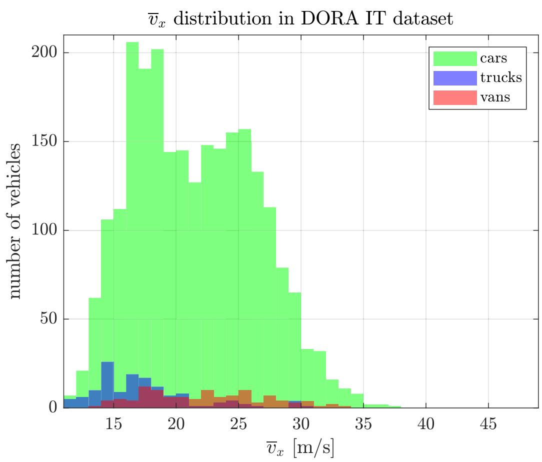

FIGURE 4. Distribution of the traffic participants' mean velocities in the Italian part of the DORA dataset.

TABLE 3. Types of vehicles in the Italian DORA dataset.

vehicle type	number	percentage [%]	$\overline{v}_x$ [m/s]
motorcycle	101	3.63	22.7
car	2429	87.28	21.5
van	111	3.99	22.3
truck	137	4.92	17.2
bus	5	0.18	19.5

vehicles are moving at lower speeds. While 58 % (1614) of the vehicles stay in the same lane, 10.35 % (288) vehicles are overtaking another vehicle, 18.47 % (514) are merging onto the highway and 13.19 % (367) of the vehicles are exiting the highway.

C. PROCESSING TOOLCHAIN

The overall pipeline to process videos into data is presented in Figure 5. In the next subsections, we describe single steps of the pipeline in more detail.

1) DRONES

For drone recording in Austria a class C/III drone was used. A special flight permission due to location and flight height was needed for legislation in 2019 when the measurement campaign started. The drone has a maximum take-off weight of 5kg, a flight time about 15 minutes and carries a professional 4K:4096 × 2160/24fps/110° field-of-view camera with active camera gimbal, see Figure 6.

For the measurements in Italy another drone, a DJI Mini2, was used, equipped with a 4K:3840 × 2160/30fps/83° field-of-view camera, see Figure 7.

2) DIGITAL VIDEO STABILIZATION

The filmed videos have a drift over the recording time mostly caused by the rotation of the drone that is not compensated by the camera gimbal. Finally, a 2-D normalized cross-correlation for pattern matching [22] with four hand chosen patterns was used. In this step the optical distortion was compensated.

3) METRIC TRANSFORMATION

In order to convert the pixel coordinates to metric system, four points and their GPS coordinates were determined and mapped to a Cartesian grid using the Haversine

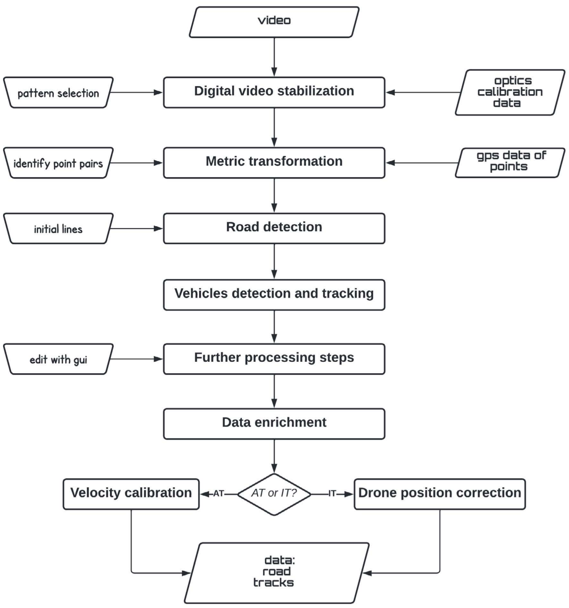

FIGURE 5. **Data post processing pipeline.**

FIGURE 6. **The drone used in Austria.**

formula for a spherical Earth of radius 6371000 m. The origin was fixed for each location. With the pixel-coordinates of these four points in a video frame, a projective fit geometric transformation to four control point pairs has been calculated.

4) ROAD DETECTION

The base for the road detection is a "mean" picture of the view, calculated during digital video stabilization. Overlaying all frames gives an empty street picture. For each lane marking three starting points are picked by hand on a black white picture of the road, for each lane marking a line is calculated optimizing the black white ratio known for the different marking types.

The lanes' center lines are defined by their left and right marking lines. The most right lane's virtual center line is used as the reference one for all other lanes of one direction. The lanes get a unique lane number/laneId: the most left lane starts with number 1, reference lane 2, acceleration strip 4, feeder lane 14, deceleration strip 3, and exit lane 13. The direction is defined by the laneId's sign, see Figure 1.

FIGURE 7. **The drone used in Italy.**

5) VEHICLES DETECTION AND TRACKING

For the detection of moving objects, a YOLOv4 network [23] has been trained and used. This version has no rotating bounding boxes and therefore the videos have been rotated making the highway horizontal. In order to accelerate the post-processing, detection regions of interest were defined where vehicles can enter the scene and exit regions where vehicles leave the scene.

Once a vehicle was detected, it is tracked using the Kalman filtering algorithm [24] including a track prediction for better performance until it leaves the scene.

6) FURTHER PROCESSING STEPS

After rotating and mapping the raw position data from detection to the Cartesian coordinate system some data processing is still needed further.

a: FILTERING WITH A VEHICLE MODEL

For each track, filtering is performed by optimizing inputs to a vehicle model following the track. The cost function penalizes high vehicles' accelerations and high steering angle deviations. For computing feasibility, a jumping time window strategy has been applied.

b: FLAGGING SUSPICIOUS TRACKS AND CORRECTION

After the previous post processing steps, suspicious tracks are automatically flagged considering abnormal velocities, road borders, intersecting tracks, double detection, etc. These tracks are then reviewed and corrected manually.

c: DATA ENRICHMENT

Several additional signals were calculated:

- the actual laneId for each point
- longitudinal and lateral positions to the reference lane
- longitudinal and lateral velocities and accelerations
- classification of the vehicles into classes: car, van, truck, (motorbike and bus)

Note that for lanes with Ids -13, -14, 13 and 14 (outside the main section of the highway) only the information in image coordinate system has been provided since the reference line becomes irrelevant for these lanes.

d: VELOCITY CALIBRATION (AUSTRIAN DATA)

In the velocity behavior of the vehicles in the Austrian data, a systematic error has been found caused by the use of the wide angle optical lens, even though it should have been compensated in the digital stabilization step. The use of a polynomial transformation with order 4 instead of the projective transformation from pixel to Cartesian coordinate system was tested but some problems with the accuracy of the 15+ point pairs still remained. To overcome this drawback, the tracks data were calibrated using the road information, i.e. that in Austria the dashed line marking between two lanes consists of 6 m long lines and 12 m gaps. This happens in the road coordinate system s/n, Cartesian coordinates were recalculated. Accordingly, the road definition was calibrated.

e: DRONE POSITION CORRECTION (ITALIAN DATA)

The YOLOv4 net was trained with bird eye view pictures from the Austrian location. The Italian scene has a 45° view resulting in a position error and different bounding box sizes. To compensate this feature the tracks data have been extended to 3D and a virtual drone position was defined, so that each data point was shifted using the detected bounding box sizes and geometric relations.

IV. COMPARISON OF DORA DATASET AND HERE API

As mentioned at the beginning, there are many different sources of traffic data. Of course, data obtained by an UAV with a fixed location are not easily compared for instance with data obtained from devices mounted on a car, but can be compared e.g. with the averaged data provided by some developer API. In this cases, we made some comparison with data derived from the HERE developer API (see Section I-C). The route requested with the HERE Routing API v7 is identical to the route that has been filmed with the drone and data are requested at the same time as the recordings with the drone have been made. The service of *DynamicSpeedInfoType* was enabled, which means that the estimated speed along the route with respect to traffic constraints is available to the user. Thus, the average speed estimated from HERE can be compared with the average speed from the post-processed drone data.

The corresponding speed values for the post-processed Italian datasets can be seen in Table 4. Most of the time, the estimated traffic speed from HERE is approximately the same as the average speed of the vehicles in the DORA dataset. In addition to the estimated traffic speed, HERE provides a maximum speed limit (which is in this location 25 m/s). The DORA dataset, however, provides much more information than the HERE developer, namely position and speed trajectories of every single vehicle. Thus, for example relative distances between vehicles and time-to-collision can be calculated to estimate the level of safety on the filmed street segment. Of course, if only average speed of traffic is needed, as for example in [14], information from HERE is obtained much easier and with less effort than filming a road segment with the drone and post-processing the data. In conclusion, depending on the specific use-case the dataset should be selected accordingly.

TABLE 4. Comparison of average traffic speed from HERE and DORA for the Italian datasets.

location	#	$\bar{v}$ HERE [m/s]	$\bar{v}$ DORA [m/s]
HWmr1	1	25.0	26.2
HWmr1	2	21.1	26.4
HWmr1	3	27.3	26.4
HWmr1	4	23.8	26.6
HWmr1	5	24.9	25.3
HWmr1	6	25.2	25.9
HWmr1	7	23.8	25.0

V. COMPARISON WITH OTHER DRONE DATASETS

A. EXISTING DRONE DATASETS

In this part we will briefly describe the existing datasets of highway entrances/exits filmed from the aerial perspective.

1) HIGHWAY DRONE DATASET (highD)

The highD [18] was, to the best of our knowledge, the first highway driving dataset of sufficient size (110 500 tracks) and high accuracy (error less than 10 cm). It was not focused on highway entrances/exits but contains 3 out of 60 recordings where the entrance has been filmed at a frequency of 25 Hz. As a result, only 76 merging maneuvers can be extracted from the highD data. Moreover, only the end part of the merging lane can be seen (see Figure 8) and therefore some early reactions of drivers on the main lane are out of the detection range.

FIGURE 8. Recording site of a merging scenario in the highD dataset.

2) INTERNATIONAL, ADVERSARIAL AND COOPERATIVE MOTION DATASET (INTERACTION)

INTERACTION [25] contains one highway merging scenario filmed in China, see Figure 9. During 95 minutes the authors recorded 10359 vehicles at a sampling frequency of 10 Hz from which 1684 merging vehicles can be extracted. Considering the above-mentioned statistics, there were over 100 vehicles per minute which corresponds to a quite dense traffic that is unusual for highways. The latter can be also illustrated by considering the distribution of the vehicles' velocities, see Figure 10. Moreover, similar to highD, only the end parts of the merging lanes have been recorded. The authors provide the users only with the image-based coordinates of the vehicles (no metric coordinates) and no statement about the accuracy of the data has been made.

TABLE 5. Comparison between the DORA dataset and existing highway exits and entrances drone datasets.

Dataset	Country	# Trajectories	# Locations	Road user types	Frequency	Flight height	Road length
highD	Germany	1482	1	car, truck	25 Hz	150 m	~400 m
INTERACTION	China	10359	1	car	10 Hz	no data	~160 m
inD	Germany	69172	7	car, van, truck	25 Hz	150 m	~440-500 m
DORA	**Austria**	2521	1	car, van, truck	24 Hz	**300 m**	**~620 m**
	Italy	2783	1	car, van, truck, **motorbike, bus**	30 Hz	120 m	~220 m

FIGURE 9. Recording site of a merging scenario in the INTERACTION dataset.

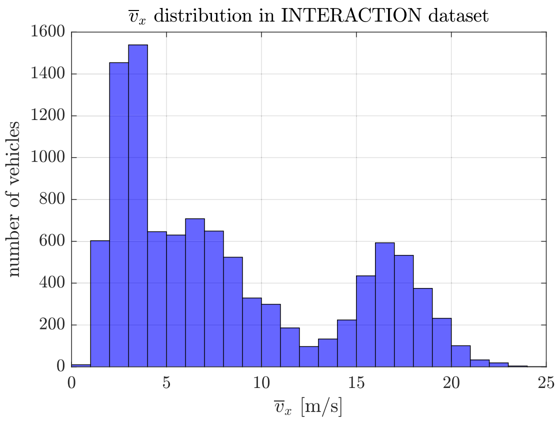

FIGURE 10. Distribution of the vehicles' velocities of the INTERACTION dataset.

3) EXITS AND ENTRIES DRONE DATASET (exiD)

The exiD [19] was introduced by the same research group as of highD in autumn 2021. At the date of writing this paper, still no accessible publication was available on the dataset. 7 locations in Germany have been filmed and in total 52621 cars, 3929 vans, and 12622 trucks were recorded at a sampling rate of 25 Hz.

B. FACE TO FACE COMPARISON

In this part, we compare the existing datasets against each other and DORA and highlight the strengths and weaknesses of our data. The summary of the comparison is provided in Table 5, where the bold features highlight the advantages of DORA. As one can see from the table, our dataset is the only one that was recorded in different countries. Moreover, the uniqueness is the flight height of 300 m in Austria and thus the visibility over 600 meters long section of the road. Concerning the data format, accuracy, and vehicles' classes the DORA dataset is comparable with highD and exiD and outperforms INTERACTION.

As a weakness of the dataset we can mention its size. Even though hours of videos have been collected, not all of them were post-processed. However, whether the size is enough or not depends on the purpose for which the data are used, for many applications even the current size of the dataset is sufficient.

VI. CONCLUSION AND OUTLOOK

In this paper we have presented a new aerial dataset DORA focused on highway exits and entrances. The dataset has been post-processed into a format that can be directly and easily used by the researchers. Moreover, the visualization tool supports the numerical data.

For some applications, the size of the dataset can be not sufficient. However, as we mentioned before, much more videos from more locations have been collected by our team. In the near future, we expect to process these videos as well and thus enlarge the DORA dataset.

ACKNOWLEDGMENT

The authors would like to thank their colleagues, Daniel Adelberger, Michael Barth, Richard Fürhapter, and Florian Meier for their help in dataset collection and post-processing. Special thanks goes to Michael Paulweber from AVL List Graz for his support and inspiration during the work.

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