Vehicle Trajectory Dataset from Drone Videos Including Off-Ramp and Congested Traffic – Analysis of Data Quality, Traffic Flow and Accident Risk

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Abstract

Vehicle trajectory data have become essential for many research fields, such as traffic flow, traffic safety and automated driving. In order to make trajectory usable for researchers, an overview of the included road section and traffic situation as well as a description of the data processing methodology is necessary. In this paper, we present a trajectory dataset from a German highway with two lanes per direction, an off-ramp and congested traffic in one direction, and an on-ramp in the other direction. The dataset contains 8,648 trajectories and covers 87 minutes and a ~1,200 m long section of the road. The trajectories were extracted from drone videos using a post-trained yolov5 object detection model and projected onto the road surface using a 3D camera calibration. The post-processing methodology can compensate for most false detections and yield accurate speeds and accelerations. We present some applications of the data including a traffic flow analysis and accident risk analysis. The trajectory data are also compared with induction loop data and vehicle-based smartphone sensor data in order to evaluate the plausibility and quality of the trajectory data. The deviations of the speeds and accelerations are estimated at 0.45 m/s and 0.3 m/s\textsuperscript{2} respectively. The trajectory data can be accessed under https://data.isac.rwth-aachen.de/

Keywords: Vehicle Trajectory Dataset; Traffic Flow; Traffic Safety; Computer Vision

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1 Introduction

Vehicle trajectory data or microscopic traffic data are highly valuable for a wide range of applications. The oldest application, starting with the famous Greenshields (1935) study, was the analysis of traffic flow and the development and validation of traffic flow models. Treiterer (1975) was among the first researchers who collected vehicle trajectories using aerial images. The second application emerged in the 1980s with the Swedish Traffic Conflict Technique, which uses vehicle trajectories to evaluate traffic safety based on Surrogate Safety Measures (SSM), e.g. Time To Collision (TTC) (Hyden and Linderholm, 1984). Whilst the vehicle movements were analyzed manually in the beginning, image processing methods helped to automatically compute SSMs and identify traffic conflicts (Messelodi and Modena, 2005). The most recent application is the development of automated driving systems, which rely on naturalistic driving data to ensure that these systems interact safely with human drivers in every possible situation (Roesener et al., 2017).

Along with the increasing number of applications, the progress in computer vision technology led to a growing number of trajectory datasets. The interest in publicly available datasets, such as the NGSIM dataset (U.S. FHWA, 2006), has shown that these datasets can be used for more than the application they were created for.

Most datasets contain only limited information on the data collection methodology and the data quality. Data quality is of high importance due to the fact that the data collection is based on position measurements, whilst most applications require velocity and acceleration. Since most datasets do not contain the raw data (videos), users of the data are not able to evaluate the data quality. The trajectory dataset presented in this paper is compared with data from an induction loop and data from a smartphone sensor that was present in one of the vehicles included in the trajectory data. By comparing the speeds and accelerations, we can estimate the accuracy of the speed and acceleration values.

Although the purpose of publishing trajectory datasets is to make them usable for other researchers, it is often difficult for them to assess whether a dataset contains a suitable road section and suitable traffic scenarios for their research question. We therefore conduct a traffic flow analysis with time-space diagrams, fundamental diagrams, and time series of flow, density and mean speed.
2 Related Work

2.1 Vehicle trajectory datasets

When searching for comparable datasets, the high requirements in the area of traffic safety analysis and the complex boundary conditions that allow an evaluation of the infrastructure should not be neglected. The investigated datasets will be compared and analyzed in this section.

The first category of datasets is generated from infrastructure-based sensors (U.S. FHWA, 2006, Cress et al., 2022, Wang et al., 2022). Here, the focus does not lie on the generation of particularly diverse data. Rather, with this kind of data generation, large amounts of data can be collected easily, e.g. for training vehicle behavior models. As the first large dataset of its kind, NGSIM (U.S. FHWA, 2006) demonstrated the possibilities of microscopic traffic data collection by placing cameras on buildings, understandably with a small amount of data and non-comparable accuracies. The dataset presented in (Cress et al., 2022) comes from a large test site of the A9 highway in Germany, which covers a 3 km stretch of highway, captured with lidar and cameras. A similar approach but using radar was taken by Wang et al. (2022), where a dataset of several kilometers of highway in China was created. All three datasets and their corresponding methodologies show promising results, but are too complex and expensive to be performed on many different routes or with little lead time and low cost.

The remaining datasets found choose a similar approach as in this work: flying drones at a very high altitude either above or directly next to the highway. For example, Krajewski et al. (2018) acquired ~16.5 hours of trajectory data from straight highway sections, in (Moers et al., 2022) additionally supplemented with on-ramps and off-ramps trajectories. The AUTOMATUM DATA dataset also provides a good basis for many applications with 30 hours of material (Spannaus et al., 2021). The MAGIC dataset focuses on using a large number of drones simultaneously and uses a commercial service to extract the trajectories, which are detrimentally longer than any other dataset thanks to the large number of drones (Ma et al., 2022).

Although all of these works are very relevant and the data can be considered for many use-cases, there is still room for improvement. The works generally rely on the road surface consisting of a single flat area with no change in elevation values. However, this approach only works as long as simple road geometries are used. The more complex the road infrastructure the larger the resulting errors will be. In contrast, this work uses three-dimensional models for the infrastructure, which allows these inaccuracies to be avoided.

2.2 Trajectory extraction methods

The generation of trajectory data has been a research topic for many years, such that a whole series of works is available. Various sensors and evaluation algorithms are used, often depending on the use case and users. For example, a fusion of several laser scanners is used for the trajectory data (Zhao et al., 2009), and in (Kloeker et al., 2020) several lidar sensors are used to capture the trajectories in an intersection. Furthermore, camera systems installed in the infrastructure can be used for recording trajectories. For example, in (Clausse et al.,
2019) a general framework with a method based on Mask R-CNN is presented for the extraction of the 3D trajectories for the use of traffic cameras.

But even when focussing on the acquisition of trajectories from drone videos, a multitude of works have already tried different methods with varying success. Azevedo et al. (2014) already recognized the possibilities of a drone based approach early on and extracted vehicle trajectories through background subtraction and a k-shortest disjoint paths algorithm for tracking at a speed of two frames per second without classification. Apeltauer et al. (2015) use the AdaBoost classifier with Multi-Block Local Binary Pattern (MB-LBP) for detection followed by the Sequential Monte Carlo method to track vehicles through an intersection. Khan et al. (2017) used the Lucas-Kanade optical flow algorithm to detect and track vehicles in combination with background extraction. Zhao and Li (2019) used Mask R-CNN for detection combined with a semi-automatic extraction of the different lanes, but lacking a description of the method for camera calibration. Kim et al. (2019) compared the results from aggregated channel feature (ACF) and Faster R-CNN for the tracking of vehicles in congested traffic situations, showing promising results despite some problems with false positive detections. Ahmadi et al. (2017) extract vehicles trajectories from space borne videos using background subtraction with a much larger field of view but with no classification and a lower precision due to the lower resolution of the videos. Masouleh et al. (2019) developed a new algorithm for the semantic segmentation of vehicles from UAV-based thermal infrared imagery using a Gaussian-Bernoulli Restricted Boltzmann Machine (GB-RBM) with improvements compared to other semantic segmentation networks. Feng et al. (2020) include pedestrians and cyclists in their Yolo v3 based approach and can therefore be used to record scenes on urban roads with all traffic participants, having an accuracy of around 92% for motor vehicles. Shi et al. (2021) used videos made from multiple helicopters to capture a larger section of a highway, simultaneously to the trajectory extraction with Yolo v3 also automatically detecting the lane markings and doing a vehicle motion characteristics calculation. Yeom and Nam (2021) approach the detection problem through the difference between two consecutive images for a driving vehicle and track the detected vehicles using a Kalman filter, sadly only using their method on a total of 22 vehicles in the recorded videos.

Furthermore, there are of course the methods already listed in the previous section about datasets, which have already proven their potential with the publication of large datasets. As one of the first applicants of neural networks for the extraction of vehicles trajectories from drone videos, Krajewski et al. (2018) used U-Net for the detection of vehicles and furthermore started the extraction of parameters of interest for the automotive industry such as maneuver classification. Using the same method, trajectories from intersections and exits were recorded in the following years (Krajewski et al., 2018, Moers et al., 2022).

Since the number of works on this topic is too large to cite them all in this work, the interested reader can be referred to two review works. In their review paper on drone based road traffic monitoring systems, Bisio et al. (2022) show further approaches and datasets also comparing the different detection and tracking algorithms used. Sadly, there is no mentioning of the different calibration methods in the reviewed papers. Butila and Boboc (2022) provide a
systematic overview of 34 works on drone based trajectory extraction, categorizing the works according to aim and feasibility.

3 Methods

3.1 Study area and material collection

The dataset presented in this paper was collected at the highway A43 near Münster, Germany. The highway has two lanes in each direction with a two-lane off-ramp in direction 1 (west to east) and a one-lane on-ramp in direction 2 (east to west). The dataset covers a ~1200 m long stretch of road during the morning peak hour (7:11 to 8:38) on 6th September 2021. Direction 1 is partly congested during this time due to a nearby on-ramp. The data were collected at two locations using drones. Two drones per location were used alternately due to limited battery capacity. As a result, there are some temporal overlaps and gaps in the videos, which have to be considered during the data processing. The drones flew 500 m above ground and each covered over 600 m of the road with a spatial overlap of ~50 m. The videos were filmed with 4K resolution (3840 x 2160), which corresponds to a vehicle size of roughly 30 x 12 pixels. Figure 3-1 shows two aerial views of the filmed road section.

![Aerial views of the filmed road section. (Top) Western part, (Bottom) Eastern Part.](image)

To check the plausibility of the vehicle trajectories derived from drone data, additional measurements were taken with a vehicle that was traveling on the highway section during the time of video recording. A smartphone’s GPS sensor and inertial measurement unit captured the vehicle’s position, speed and acceleration with a frequency of 1 Hz (position and speed) and 100 Hz (acceleration) respectively. The smartphone was mounted on a flat surface approximately at the center of the vehicle to ensure that it remained aligned in the vehicle coordinate system at all times. The data was collected with an iPhone X and the app PhyPhox that allows recording of raw sensor data (Staacks et al., 2018). To assure that the vehicle is easily visible in the video images, an orange van (VW Transporter) was used. This ensures that the drone data can be correctly assigned to this vehicle and that drone and vehicle data can be compared correctly.

3.2 Trajectory extraction

Stabilization

The first step in evaluating drone images is usually video stabilization. Since the calibration step explained in the next section can only be performed on the first frame of each video, each
subsequent frame in the video is transformed to match this first frame. The stabilization is performed based on a standard pipeline using the feature detection from Shi and Tomasi (1994), the Lucas-Kanade feature tracking method presented in (Bouguet, 2000), and the computation of a homography via RANSAC. If the computation of the homography is successful, the current image can be deformed accordingly. In case of particularly abrupt movements of the drone or continuous displacement of the image and thus too large a deviation, stabilization is interrupted and the video is split, removing up to two seconds of video to eliminate any blurred images. Editing of the video is initiated in the event that less than 5% of the features found can be recovered by homography.

**Calibration**

Calibration of the video corresponds to the process of finding a transformation matrix for converting 2D image coordinates to 3D world coordinates. For this purpose, the first step is to create a 3D model of the road markings using publicly available geodata (georeferenced orthophotos and an elevation model from laser scanner data) from North Rhine-Westphalia (Geoportal NRW) (see Figure 3-2). Since the resulting model does not show a single straight road surface as in other works, but a more realistic 3D surface, it is approximated with triangulation. Instead of calculating a single transformation for the entire road surface, as is usually the case, in our case each triangulation surface receives a separate transformation. With the 3D model, reference points can be captured and the different transformations computed in a final step.

![Figure 3-2: 3D-Street-Model of the recorded highway segment, color-coded according to the z axis.](image)

**Detection and Tracking**

The detection of vehicles in single frames is done with a post-trained model based on yolov5 (Jocher et al., 2022). For this purpose, several minutes of video footage were labeled by hand and used via transfer learning to adapt an existing model. The trained model provides excellent results in detecting vehicles, a slight tendency to false-positive detections can be remedied in the future via further training, in our case the false detections are reliably eliminated via tracking and post-processing of the trajectories. Accordingly, in the present work not the single detections are a criterion of the data quality, but rather the complete trajectories (see Results and Discussion chapter). The creation of these trajectories happens in the first step by matching the positions and the driving direction. In all further steps, no longer the distance between two detections is determined, but the distance between the current position and the position predicted on the basis of the speed recorded so far. Kuhn-Munkres (Munkres, 1957)
is used as the matching algorithm. Figure 3-3 shows a snapshot of a drone video with the vehicle detections re-projected into the image.

Figure 3-3: Snapshot of a drone video with vehicle detections.

3.3 Data Processing

Data processing ensures that the vehicle trajectories are plausible and that the trajectories extracted from each video are joined to a single dataset.

The first step is to convert the vehicle positions from world coordinates to road coordinates, i.e. a coordinate system where the x-axis lies on the right edge of the rightmost lane and the y-axis is orthogonal to the x-axis. Thus, the x value represents the distance travelled by a vehicle and the y value represents the distance to the right edge of the road, which can be used to determine the lane on which the vehicle drives. This coordinate system is convenient for most applications involving inter-urban roads, where all vehicles drive in the same direction, and mostly only the velocities and accelerations in driving direction are relevant. The road markings were extracted as polygonal chains from georeferenced orthophotos (see Calibration section) and then smoothed.

The road coordinates are also useful to check the plausibility of the data. It can be assumed that vehicles only drive forward, i.e. the velocity in x-direction must not be smaller than zero. It can also be assumed that the velocity has an upper bound. Therefore, the difference between two subsequent x values (Δx) is a criterion for plausibility. The difference between two subsequent y values should be limited more strictly as lateral velocities are usually much smaller than longitudinal velocities. A large time gap between two subsequent data points of the same vehicle is another criterion that has also proven to be a criterion for implausibility. The implausible points are removed from the data, and then the plausibility is checked again with the remaining data points. This procedure is repeated several times in order to remove all single outliers. If there are implausible points in a trajectory remaining after 10 iterations, the points of this trajectory might not all belong to the same vehicle. The trajectories are therefore split at the remaining implausible points, i.e. a new vehicle ID is assigned to one part of the trajectory. Figure 3-4 shows that most obvious errors in the data can be removed by this method.
In order to obtain realistic velocities and accelerations, the trajectories are then smoothed by fitting a smoothing spline to the data. The smoothing parameter has to be selected depending on the magnitude of the outliers that have not been removed during the plausibility check. In our dataset, a smoothing parameter of 0.2 in x-direction and 0.5 in y-direction has shown to be suitable. Figure 3-5 shows that this process can successfully remove the outliers.

Next, the trajectories extracted from different videos are joined. Since the timestamps of the videos are not perfectly synchronized, the trajectories have to be shifted temporally by a few seconds. Since the number of videos is not too high, this step can be performed manually. The trajectories of two adjacent (spatially or temporally) videos are plotted with different shift values, and the best fit is selected (see Figure 3-6).
Figure 3-6: Identifying the shift between two adjacent (temporally or spatially) videos.

Figure 3-4 and Figure 3-6 show that many vehicles are represented in the data by more than one trajectory. Therefore, overlapping or adjacent trajectories that belong to the same vehicle have to be identified and joined. If the distance in x-direction is smaller than 5 m and the distance in y-direction is smaller than 2.5 m, the trajectories are considered as overlapping. In this case, one of the trajectories is removed. If the last point of one trajectory and the first point of another trajectory are closer than 10 m in x-direction and 3 m in y-direction, they are joined as they likely belong to the same vehicle (see Figure 3-7). The joined trajectories are then smoothed again. Short trajectories (< 3 s) are removed from the dataset as they are likely false positive detections as mentioned above.

Figure 3-7: Raw data (red) and trajectories after all data processing steps (blue).
4 Results and Discussion

The dataset contains 5,016 trajectories in direction 1 and 3,632 trajectories in direction 2. Regarding the sensitivity of the recorded data, a random sample analysis of about 450 vehicles shows that only about 0.45 % of the vehicles actually present were not detected. These vehicles are gray, hence their contrast to the road pavement is very small. False detections could not be identified in the sample, mainly due to the trajectory post-processing, which removes any too short trajectories. In direction 1, 3,993 trajectories (79.5 %) are longer than 90 % of the length of the filmed road section (direction 2: 2,928 trajectories, 80.6 %). The remaining vehicles are represented in the dataset by two or more shorter trajectories with small gaps that could not be filled by the data processing methodology. These shorter trajectories can still be used for traffic flow and accident risk analyses.

4.1 Description of the dataset

We provide the data in two different formats: for Matlab users in .mat format and for all other users in .csv format.

In the .mat format, the data is provided in a cell array where each cell contains the data of a single vehicle. The data of a single vehicle are organized in a structure array (“struct”). The struct contains time-dependent and time-independent data. The time-independent data include the vehicle ID, a description of the vehicle category (passenger car, bus, truck etc.) and a corresponding ID of the vehicle category, the vehicle length and width in [m], the 2D-contour (n-by-2 table, where X=0 and Y=0 is the vehicle centroid). The time-dependent data include the trajectory. The original (unprocessed) trajectory is a n-by-6 table with vehicle ID, 2D-positions in the road coordinate system in [m] (x is the direction along the road, y is orthogonal to x), timestamp in [s] (starting at 06-Sep-2021, 6 a.m.), and 2D-positions in the global UTM coordinate system. The fitted (processed) trajectory is a n-by-3 table with 2D-positions in the road coordinate system and timestamps, and a n-by-3 table with 2D-speeds in the road coordinate system and timestamps, and a n-by-3 table with 2D-accelerations in the road coordinate system and timestamps.

For Matlab users, we also provide a small toolbox which enables some basic analyses and visualizations.

In the .csv format, the data is provided in a table with the following columns: timestamp in [s] (starting at 06-Sep-2021, 6 a.m.), timestamp in “yyyy-MM-dd HH:mm:ss.S” format, vehicle ID, a description of the vehicle category (passenger car, bus, truck etc.), vehicle length and width in [m], and the fitted (processed) trajectory with the 2D-positions in [m], 2D-speeds in [m/s] and 2D-accelerations in [m/s²] in the road coordinate system in [m] (x is the direction along the road, y is orthogonal to x).

The dataset and the Matlab toolbox can be downloaded here: https://data.isac.rwth-aachen.de/

4.2 Traffic flow analysis

In the following, we present a microscopic and macroscopic traffic flow analysis based on the trajectory data. Figure 4-1 shows two time-space diagrams of an excerpt of the data. Color-
coding the lanes (Figure 4-1 left) illustrates the frequency and locations of lane changes, the gaps between vehicles and the speed differences between the lanes. Color-coding the speed (Figure 4-1 right) illustrates the propagation of shock waves.

The time series of flow, density and mean speed in 1-min-intervals (see Figure 4-2) allows the identification of congestion and the distribution of the vehicles between lanes. There are two stop-and-go waves (7:46 and 7:53) with large densities and small speeds on both lanes. Due to the small length of these stop-and-go waves, the flow does not decrease significantly. As expected, the mean speed on lane 2 is larger than on lane 1 due to slower trucks on lane 1.

The flow-density-diagram, speed-flow-diagram, and speed-density-diagram (see Figure 4-3) show the capacity, the optimal speed, and the critical density on this road section. Again, the small length of the stop-and-go waves leads to densities up to 57 veh/km per lane, which is well below the maximum jam density.

Figure 4-1: Time-space diagrams with color coded lanes (left) and speeds (right).

Figure 4-2: Time series of flow, density and mean speed.
Figure 4-3: (Left) Flow-density-diagram, (Center) speed-flow-diagram, (Right) speed-density-diagram.

4.3 Accident risk analysis

The concept of traffic conflict analysis is based on the assumption, that each traffic interaction can lead to a collision. The lesser chance the participants of a traffic interaction have to react and avoid the crash, the more dangerous the situation is evaluated. To determine this “closeness” to a crash, different surrogate safety measures (SSM) were developed in the last decades. According to Mahmud, these SSMs can be categorized as follows: 1.) Temporal-proximal indicators 2.) Deceleration-based indicators and 3.) Distance-based proximal indicators (Mahmud et al., 2017).

From the first two categories, Time-to-Collision (TTC) and Deceleration Rate to Avoid Crash (DRAC) are two of the most used measures to analyze traffic safety. Both of these SSMs rely on the assumptions that the analyzed traffic participants would maintain their course and momentum from an initial moment until the collision would happen. This way, TTC determines the remaining time until the collision from this initial moment, whereas DRAC estimates the smallest deceleration rate needed to avoid the collision (Hayward, 1971, Almqvist et al., 1991).

However, both in inner-city traffic and on highways acceleration and deceleration of the traffic participants cannot be neglected. Therefore, to evaluate the traffic on the recorded road section, we applied the modified versions of these two indicators: we used modified time-to-collision (MTTC) and deceleration rate to avoid crash using constant initial acceleration (DCIA). MTTC was developed by Ozbay et. al. (2008) and can be calculated as follows:

\[
MTTC = \begin{cases} 
\frac{D}{v_d}, & \text{if } v_d > 0 \text{ and } a_d = 0 \\
\frac{-v_d \pm \sqrt{v_d^2 + 2a_dD}}{a_d}, & \text{if } a_d \neq 0
\end{cases}
\] (1)

where \(v_d = v_F - v_L\) is the initial speed difference between follower and leader vehicles, \(a_d = a_F - a_L\) is the acceleration difference, and \(D\) is initial net distance between the vehicles. MTTC is the smallest positive result. In case MTTC is equal to or lower than 1.5 s, the interaction is considered as risky (Ozbay et al., 2008).

DCIA was developed by Fazekas et al. (2017) and can be calculated as follows:

\[
DCIA = \frac{d_L T + v_L - d_F R - v_F}{T - R}, \text{ if } T > R
\] (2)
where $v_F$, $v_L$, $d_F$, and $d_L$ are the initial speed and initial deceleration values of follower and leader vehicles. $R$ is the reaction time of the follower vehicle. $T$ is the time until crash, which can be calculated as follows:

$$T = \frac{v_F R - v_L R - 2D}{v_L + d_L R - v_F - d_F R} \text{ if } \text{denom.} \neq 0$$

(2)

In case DCIA value is above 3.4 m/s$^2$, the interaction is considered dangerous (Fazekas et al., 2017).

Due to the traffic data collection method described above, SSMs can be calculated at any timestamp in this dataset. This allows to determine the extreme values of TTC and DCIA between interacting vehicles, which enables the analysis of the whole traffic scene. For this purpose, we built so-called pairs of interacting vehicles (one follower and one leader vehicle), which had the possibility to collide based on their momentum. In the case of MTTC, we then determined the lowest value of each vehicle pair, whereas for DCIA we identified the highest deceleration rates between the paired vehicles. As next step, we located these extreme values on the position of the follower vehicles on the road. Then we calculated the average value of these results in each 20 m long section on the analyzed road section, on each traffic lane separately. To present only relevant information, we only considered MTTC values under 5 seconds. Accordingly, Figure 4-4 shows the result of average MTTC and Figure 4-5 shows average DCIA values on travel direction west to east. The values are presented with colors: the riskier the interaction based on the SSM, the darker the red is.

![Figure 4-4: Average MTTC values under 5 s in 20 m long sections on travel direction west to east.](image)
The average MTTC values lie under the threshold value of 1.5 s on the main lane (lane 1) in 23% of the 20 m long road sections, on the passing lane (lane 2) in 27.9% and on the first exit lane (lane 0) 18.2%. In contrast to MTTC, the average DCIA values did not reach the threshold value of 3.4 m/s² on the road section. The results can be explained by the congested traffic, where vehicles are relatively close to each other, therefore the time to a crash is low, while due to lower speed values traffic participant do not need to brake strong to avoid a collision.

4.4 Macroscopic comparison with induction loop data

Using data from nearby induction loops, the flow and mean speeds computed with our dataset can be compared to the flow and mean speeds measured by the induction loops. First, we use data from two induction loops (one on each lane, only direction 1) that are located in the middle of the filmed road section. Figure 4-6 shows that the both the flows and the mean speeds from the drone dataset are consistent with the flows and mean speeds from the induction loop data. However, the flows from the drone dataset are mostly a little smaller, which indicates that not all vehicles have been detected. The root mean square (RMS) deviation of the flows is 2.2 vehicles per minute on lane 1, and 3.1 vehicles per minute on lane 2. The speeds from the drone data are also mostly a little smaller. The RMS deviation of the speeds is 0.78 m/s (2.8 km/h) on both lanes. Since the accuracy of the speed measurement of the induction loops is unknown, it cannot be concluded which values are more accurate.
The data from the adjacent induction loops can be used to interpolate the mean speeds in the filmed road section. Due to the propagation of shock waves (forwards in free flow conditions and backwards in congested flow conditions), a linear interpolation is not appropriate. Instead, we use the Adaptive Smoothing Method (ASM) proposed by Treiber and Helbing (2002), which takes the propagation of shock waves into account. Figure 4-7 shows a good agreement between the mean speeds obtained from the trajectory data and the interpolated mean speeds obtained from the induction loop data.

![Figure 4-7: Comparison of mean speeds obtained from induction loop data and the Adaptive Smoothing Method (left) and the mean speeds obtained from our trajectory data (right).](image)

The induction loops categorize the vehicle flows into passenger cars and trucks. In direction 1, the truck ratio is 8.2% (direction 2: 10.5%) according to the induction loop data and 12.3% (direction 2: 11.5%) according to the trajectory data. These differences indicate that some passenger cars might have been falsely labelled as trucks in the trajectory data. However, the accuracy of the vehicle categorization in the induction loop data cannot be validated.

### 4.5 Microscopic comparison with in-vehicle sensor

To check the plausibility of calculated speeds and accelerations obtained from drone data, eight test runs with in-vehicle sensors were made, four in each direction. Similar to the drone data, in-vehicle data were smoothed to reduce signal noise. A smoothing spline with break points of 0.5 seconds for the accelerometer and 2 seconds for the GPS was used. These parameters were chosen to filter out sensor noise without compromising the validity of the data. For a valid comparison between drone data and in-vehicle data, the clocks of both data sources were aligned based on the position data. The signals of in-vehicle sensors were shifted by the time difference between drone and in-vehicle sensor data at the position where the measurement vehicle was first detected by the drone.

Figure 4-8 shows good agreement of speeds derived from drone data and speeds obtained from in-vehicle sensors. The deviations between the signals of the two data sources are normally distributed with the mean at 0.01 m/s and standard deviation 0.47 m/s. Thus, no systematic deviation can be identified. The mean correlation between the signals are 0.99 (direction 1) and 0.90 (direction 2). The root mean square (RMS) deviations between the signals are on average 0.43 m/s (direction 1) and 0.46 m/s (direction 2).
Figure 4-8: Comparison of the speeds of the measurement vehicle obtained from drone data (blue lines) and from in-vehicle data (orange lines) of eight test runs (left: direction 1, right: direction 2).

Accelerations are compared in travel direction (x-direction) and orthogonal to travel direction (y-direction). The general patterns of drone data and in-vehicle sensor data are similar in both x-direction (Figure 4-9) and y-direction (Figure 4-10), which is also indicated by low average RMS deviations (see Table 4-1). However, high frequency changes in acceleration cannot be detected in the drone data. This is particularly noticeable in y-direction. Lane changes are clearly recognizable as peaks with in-vehicle data while the signal derived from drone data is substantially smoothed out. This is also reflected in a low correlation in y-direction between the two data sources. In addition, there is an offset in x- and y-directions which changes between runs. This could be due to small movements of the smartphone mount between runs as the offset is constant during each test run.

Table 4-1: Parameters for comparing acceleration data derived from drone data and acceleration data obtained from the in-vehicle sensor.

<table>
<thead>
<tr>
<th>Signal</th>
<th>Mean of deviations [m/s²]</th>
<th>Std.-Dev. [m/s²]</th>
<th>Correlation [-]</th>
<th>Average RMS deviations [m/s²]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acceleration in X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direction 1</td>
<td>0.23</td>
<td>0.25</td>
<td>0.83</td>
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<td>Direction 2</td>
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<td>0.80</td>
<td>0.28</td>
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<tr>
<td>Acceleration in Y</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>0.20</td>
<td>0.45</td>
<td>0.20</td>
</tr>
<tr>
<td>Direction 2</td>
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<td>0.26</td>
<td>0.36</td>
<td>0.26</td>
</tr>
</tbody>
</table>
Compared to the speed differences between induction loops and drone data, the differences between in-vehicle data and drone data are substantially smaller. This indicates that the induction loops on this section of the road might not be well calibrated for speed measurements. The comparison with the in-vehicle data confirms therefore the high quality of the drone data.

5 Conclusions

This paper presented a vehicle trajectory dataset from a German highway with two lanes and an off-ramp as well as the methods implemented to create the dataset. The data contain both free and congested traffic. The data extraction and processing methodology is applicable to other drone videos and, to some extent, to videos from stationary cameras. We performed a traffic flow analysis and an accident risk analyses, which showed that the trajectory data are suitable for these two applications. We also evaluated the plausibility and quality of the data by comparing the speeds, accelerations and flows with the results from induction loop data and smartphone accelerometer data. The results showed a good agreement between our
dataset and the other sensor data, which indicates a good data quality. We therefore conclude that the dataset is usable for traffic flow and traffic safety analyses.

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**Author Contributions**

The authors confirm contribution to the paper as follows: study conception and design: M. Berghaus, S. Lamberty, E. Kallo, J. Ehlers, M. Oeser; data collection: S. Lamberty; analysis and interpretation of results: M. Berghaus, E. Kallo, J. Ehlers; draft manuscript preparation: M. Berghaus, S. Lamberty, E. Kallo, J. Ehlers. All authors reviewed the results and approved the final version of the manuscript.

**References**


Almqvist, S., Hyden, C., and Risser, R. Use of speed limiters in cars for increased safety and a better environment. Transportation Research Record, 1991


Berghaus, M., Lamberty, S., Ehlers, J., Kallo, E., Oeser, M. Vehicle Trajectory Dataset from Drone Videos Including Off-Ramp and Congested Traffic. Download link to the dataset presented in this paper, 2022. [https://data.isac.rwth-aachen.de/](https://data.isac.rwth-aachen.de/)

Bouguet, J. Pyramidal implementation of the Lucas Kanade feature tracker. Intel Corporation, Microprocessor Research Labs, 2000


Clausse, A., Benslimane, S., and De La Fortelle, A. Large-Scale extraction of accurate vehicle trajectories for driving behavior learning. IEEE Intelligent Vehicles Symposium (IV), 2019


Geoportal.NRW. https://www.geoportal.nrw/


Hayward, J.C. Near misses as a measure of safety at urban intersections. Pennsylvania State University, Dept. of Civil Engineering, 1971.


Krajewski, R., Bock, J., Kloeker, L., and Eckstein, L. The highD Dataset: A Drone Dataset of Naturalistic Vehicle Trajectories on German Highways for Validation of Highly Automated Driving Systems. 21st International Conference on Intelligent Transportation Systems (ITSC), 2018

Ma, W., Zhong, H., Wang, L., Jiang, L., and Abdel-Aty, M. MAGIC Dataset: Multiple Conditions Unmanned Aerial Vehicle Group-Based High-Fidelity Comprehensive Vehicle Trajectory Dataset. Transportation Research Record: Journal of the Transportation Research Board, 2022


Ozbay K, Yang H, Bartin B, and Mudigonda S. Derivation and Validation of New Simulation-Based Surrogate Safety Measure. Transportation Research Record, 2008, 2083(1):105-113


Shi, X., Zhao, D., Yao, H., Li, X., Hale, D. K., Ghiasi, A. Video-based trajectory extraction with deep learning for High-Granularity Highway Simulation (HIGH-SIM). In: Communications in Transportation Research 1, 2021, p. 100014

Spannaus, P., Zechel, P., and Lenz, K. AUTOMATUM DATA: Drone-based highway dataset for the development and validation of automated driving software for research and commercial applications. IEEE Intelligent Vehicles Symposium (IV), 2021


Zhao, D., and Li, X. Real-World Trajectory Extraction from Aerial Videos - A Comprehensive and Effective Solution. The 2019 IEEE Intelligent Transportation Systems Conference - ITSC, 2019