Field Investigation of Vehicle Acceleration at the Stop Line with a Dynamic Vision Sensor

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Abstract: This article presents a study of vehicle acceleration distribution at a traffic signal stop line in an urban environment. Accurate representation of vehicle acceleration behavior provides important inputs to traffic simulation models especially when traffic related emissions need to be estimated. A smart eye TDS (traffic data sensor) system was used to record vehicle trajectories, which were extracted to calculate vehicle acceleration profiles. This paper presents the acceleration distributions obtained from over 300 passenger-car acceleration cycles observed on site from the stop line up to a maximum speed of 40 km/h. These distributions are compared with the outputs from a traffic micro simulation tool modeling a similar stop line scenario. The comparison shows that measured accelerations present wider distribution and lower values than the micro simulation. This result highlights the importance of using acceleration distribution calibrated with real-world measured data rather than default values in order to estimate accurate emission levels.

Key words: Traffic data sensor, vehicle acceleration behaviour, acceleration profile, traffic micro simulation.

1. Introduction

The rationale for investigating vehicle acceleration is driven by the growing need to combine traffic simulation with the modeling of emissions caused by traffic. The pollutant emission rates of a vehicle are strongly dependent on the magnitude of its acceleration. Current traffic simulation software tools rely on predefined acceleration models. Typically, default parameter values are used and amended to ensure realistic representation of traffic operations (e.g., junction capacities) rather than being calibrated to ensure accurate representation at the individual vehicle level. In instances where calibration of the acceleration profile for a specific road network does occur, usually rather limited field data are used (e.g., from floating car techniques).

Inaccurate representation of vehicle acceleration behavior in traffic micro simulation models has been identified as a significant source of uncertainty in emissions predictions in several studies [1-4]. Accurate real-world measurement of vehicle acceleration trajectories is required to ensure the model which is appropriately calibrated and able to produce realistic emission estimates for the traffic situation being studied. Innovations in sensing technologies can be used to provide locally-relevant calibration parameters for acceleration in traffic models.

Previous research studies into vehicle acceleration have suggested that there are inconsistencies between reality and microscopic models [4]. In this study, high resolution camera images were used to extract vehicle trajectories at a signalized intersection in Rotterdam, the Netherlands. The study compared the real-world measurements with simulated data from microscopic simulation software. The results showed that the speed and acceleration estimates from the simulation model

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were much higher than real-world data. It is indicated that drivers accelerate with much more variation in the real world than in the simulations with values measured in the range 0 to 5 m/s². Another study undertaken by Hirschmann et al. [5] has used high time resolution GPS (global positioning system) to obtain the vehicle trajectories on an urban signalized corridor. The vehicle position was recorded at a rate of 20 Hz, so that the vehicle acceleration activity could be studied. The study showed that the desired acceleration rates from the VISSIM (“VerkehrInStädten—SIMulationsmodell”, German for “Traffic in Cities—Simulation model”) simulation model are too high by default, and suggested that these parameters need to be calibrated against the real-world measurement before the model can be used for emissions estimation. The acceleration values determined from this study are from 0 to 4 m/s².

Other research into the vehicle acceleration at signalized junctions [6-8] has focused on developing different models for estimating acceleration rates. In Ref. [7], the study proposed a vehicle dynamic model for predicting maximum acceleration for passenger vehicles. The model predicted values of acceleration range between 0 and 4.3 m/s² for the tested vehicles.

The “smart eye” TDS (traffic data sensor) used for the vehicle trajectory recording and analysis presented in this paper overcomes some of the practical limitations of conventional video processing methods, such as limited dynamic range and non-real time processing. A specialized optical dynamic vision sensor [9] delivers zero-redundancy, asynchronous data containing precise timing information of moving objects. This device features a 1 ms temporal resolution and wide dynamic range of 120 dB of illumination. The raw data rate of this sensor is relatively low compared to conventional video due to its on-chip data compression mechanism. The analog pre-processing of the visual motion information on the sensor focal plane suppresses the static background and allows for a

sparse representation of the vehicle trajectory. Unlike a conventional video based sensor, the smart eye sensor is capable of on-board, real time vehicle detection and speed measurements on up to four lanes simultaneously have been presented in previous publications [10-14]. The important aspect of the work presented here is that the TDS device is capable of a continuous, long-term road side deployment whereas the video-based approaches found in literature are typically not. Video techniques often lack of real time processing capabilities and typically do not have sufficient dynamic range for day and night operations or operations under all weather and lighting conditions.

In the work presented in this paper, the raw sensor data have been utilized to record and analyze the full trajectories of the vehicle and the recorded data have been processed offline using MATLAB. The major contribution of the work is to use this special high time resolution, optical sensor technology for acceleration measurement, which provides very accurate data to calibrate vehicle acceleration profiles.

The results will be used in the traffic micro simulation that serves as a basis for a decision support tool for adaptive traffic management developed by the CARBOTRAF (a decision support system for reducing CO₂ and black carbon emissions by adaptive traffic management) project within the European 7th Framework Programme. The CARBOTRAF project aims to support traffic operators in real time when choosing the most effective ITS action to reduce CO₂ and BC (black carbon) emissions.

The article is organized as follows: Section 2 describes the vision sensor and field setup; Section 3 explains the method of acceleration calculation; Section 4 describes the traffic micro simulation that was performed in order to compare with the field results; in Section 5, the acceleration results are presented and compared with those obtained by the micro simulation; Section 6 provides the conclusions of the study.

2. Sensor System and Field Setup

In this section, the smart eye traffic sensor and the road setup for the vehicle trajectory recording are described. In contrast to traditional semiconductor CCD (charge-coupled device) or CMOS (complementary metal-oxide-semiconductor) imagers that encode image irradiance and produce constant data volume at a fixed frame-rate irrespective of scene activity, the sensor contains an 128×128 arrays of autonomous, self-signaling pixels which individually respond to relative changes in light intensity. Pixels respond by placing their address on an asynchronous arbitrated bus with a latency of less than 100 μ s, generating the so-called “events”. Pixels that are not stimulated by a change in illumination are not triggered, hence static scenes produce no event output. Because there is no pixel readout clock, no time quantization takes place at this point. The sensor operates largely independent of scene illumination, directly encodes object reflectance, and greatly reduces redundancy while preserving precise timing information. Because the output bandwidth is automatically dedicated to the dynamic parts of the scene, a robust detection of fast moving vehicles is achieved. The high dynamic range of the photosensitive element (> 120 dB or 6 decades) makes the sensor well-suited to applications under uncontrolled light conditions.

The pixel locations (i, j) in the imager array are encoded in the data by AER (address-event-representation) [15], as shown in Fig. 1. The scene information is transmitted event by event and stored to a binary data file as 16-bit addresses and corresponding time stamps with a 1 ms time resolution. This corresponds to a 1,000 frames per second imaging when compared with a conventional video sensor.

The traffic sensor is capable of detecting and transmitting 100,000 illumination changes per second (100 kilo “events” per second, keps) and more. However, for a typical traffic surveillance scenario, the peak data rate from the 128×128 pixel imager is not higher than 50 keps on average. Fig. 1 shows a visual

reconstruction of four image frames from the AER data as seen from the sensors perspective. The four frames taken with a 20 ms time difference contain two moving vehicles. The vehicles front sections with headlights and bonnet can be distinguished (indicated by “H” and “B” in Fig. 1).

In contrast to the studies mentioned above, which used video equipment mounted on a high tower 100 m above the road [4] or high time resolution GPS installed in a set of test vehicles [8], this study uses a device that can be easily integrated into existing road side infrastructure and can capture vehicles under normal operation, as shown in Fig. 2. Field investigation thereby becomes simpler to implement, and more representative of the actual traffic conditions.

Fig. 1 A sequence of four image frames reconstructed from the asynchronous AER data showing two moving cars from the traffic sensors perspective.

The time difference between the four frames (a)-(d) is 20 ms. Black pixels in these images represent changes from bright to dark, white pixels represent changes from dark to bright. In the reconstructed images, the bonnets (B) and headlights (H) of the cars can be distinguished in frames (a) and (c). The image plane coordinates (i, j) are indicated in the second frame (b). In frame (d), the dashed lines mark the lane boundaries of the monitored lane (L).

Fig. 2 (a) Field setup at the signalized intersection in the Vienna urban area; (b) important mounting parameters and the world coordinate system.

The processing capability of the embedded sensor system furthermore offers the possibility to implement the acceleration sensing directly in the device, serving future traffic management systems to ingest live acceleration data from the road network at locations of interest.

Fig. 2a shows the setup at the traffic light at a signalized junction in the Vienna urban area. The sensor field of view covers three lanes of the four lanes of the street. The data from one lane were used for this analysis. The sensor is mounted overhead, above the monitored lane on a sign bridge and faces upstream, into the traffic flow. The stop line is located 4.6 m upstream of the sensor position. The sensor is mounted at a height h of 5.6 m above the road surface at a viewing angle β of 62° against the normal. The world coordinate system (x, y) applied to the data after rectification is indicated in Fig. 2b. Although the sensor field of view covers three lanes, only the vehicles driving in the center lane (directly underneath the sensor) have been used for this evaluation study. This lane is marked as “straight ahead only”, with no turning vehicles. The reason why data from other lanes have not been used for this study is that only this lane is completely covered by the sensors field of view (lane indication “L” in Fig. 1). Fig. 3a shows a typical example of an AER vehicle trajectory data as recorded by the sensor in space-time representation. The trajectory for a vehicle approaching the sensor is shown in a space-time representation, with i and j being the

horizontal and vertical axes in image space (compared with axes indication in Fig. 1), respectively.

Using the known camera parameters of the sensor, the AER data are rectified to the world coordinate system where vehicle trajectory is represented as distance from the sensor and function of time. Fig. 3b shows the full trajectory (top) and extracted leading edge (bottom). This leading edge represents the front part of the vehicle.

From the leading edge of the trajectory, the space-time representation of the vehicle trajectory is obtained, from which speed and acceleration are derived. Traffic counting and speed measurement of TDS were previously validated using manual counts from video recordings and speed measurements [14, 15].

3. Acceleration Calculation

Trajectories were annotated from their arrival approximately 13 m upstream from the sensor position, corresponding to a zone from about 7 m upstream to about 0.5 m downstream the stop line (6 m from the sensor position).

The first three cars passing the stop line after green have been included in the investigation, ensuring that only accelerating vehicles are added to the database. To implement this annotation, a MATLAB based graphical user interface has been developed that allows the addition of trajectories and other relevant vehicle parameters, such as vehicle class, to a common database of vehicle trajectories.

Fig. 3 (a) Address event representation of a vehicle trajectory in image space (in pixel), i horizontal axis, j vertical axis; (b) extracted and rectified address event data of the trajectory in world coordinate space x (in m).

Fig. 4 shows a screenshot of the main window of the annotation tool. The upper axis presents a rough reconstruction of the vehicle top view from the AER data (“2” in Fig. 4) to the user allowing classification of the vehicle into different size categories (“1” in Fig. 4). The lower axis presents the reconstructed trajectory in space-time where the AER activity is rendered for imager coordinate j versus time (“3” in Fig. 4). Bright lines in this axis indicate strong bright edges of the vehicle, dark lines indicate dark edges of the vehicle, grey areas indicate unchanged background. This AER activity “image” is a histogram of the event activity per time unit. The temporal resolution at this reconstruction is 10 ms corresponding to an equivalent frame rate of 100 frames per second when compared with conventional video data. The annotation is performed by locating several points (“4” in Fig. 4) along the track of the leading edge of the vehicle with the mouse cursor, thereby reconstructing the path in the image space.

The user input for the given example is indicated in

Fig. 4 by white crosses. Typically 3~10 trajectory segments with a sampling interval of 0.1 s to 0.6 s have been annotated per vehicle trajectory. Manual annotation has been chosen in preference to an automated extraction of the trajectory points at this stage to ensure data quality for this study. Furthermore, these data are intended to be used as ground truth test cases for the acceleration detection in the embedded traffic sensor device.

The speed and acceleration have been calculated for the individual segments after the transformation from image (pixels) to world coordinates (meters). In total, 323 trajectories with 966 segments have been evaluated.

4. Traffic Micro Simulation of Stop Line Accelerations

Using state-of-the-art PTV (Planung Transport Verkehr AG) VISSIM traffic simulation software [16], a number of vehicles accelerating from the stop line have been simulated.

Fig. 4 Screenshot of the annotation tool user interface with indication of important elements.

1: Annotation of auxiliary information such as vehicle class; 2: reconstructed top view of the vehicle; 3: vehicle trajectory in space-time (t, j) representation; 4: white crosses represent user input for the trajectory annotation.

A microscopic simulation model has been developed to replicate the traffic operations of the junction in Vienna measured by the smart eye TDS traffic sensor. One signalized junction is coded in the simulation with a cycle time of 60 s, and a detector is installed 16 m upstream from the stop line to measure the arriving vehicles. Along with the vehicle record files from VISSIM, vehicles entering a detection zone corresponding to the field of view of the traffic sensor are filtered out. Only the first three vehicles passing the stop line after green have been included in the study.

The key configuration parameters in VISSIM are set as per Table 1.

For the purpose of this study, there are only two types of vehicles specified in the simulation: cars and HGVs (heavy goods vehicles). For each vehicle type, the desired speed distribution is specified in the simulation. In VISSIM, a stochastic distribution of desired speed is defined and the range of distribution is also specified by a minimum and maximum speed shown in Table 1. The simulation duration was set as 1

h, excluding 30 min simulation warm-up time at the beginning.

The speed and acceleration of each individual vehicle are recorded at 10 Hz frequency in the simulation. This provides sufficient resolution for the acceleration trajectory analysis in this study. All default parameters are used in the simulation (such as desired speed and acceleration) in order to compare the real-world vehicle dynamics with the modeled. This is a limitation of the study as these parameters can affect acceleration and deceleration. The dataset used for the analysis contains 1 h of simulation which results (after data processing and filtering) in about 200 vehicle trajectories.

5. Results

5.1 Speed and Acceleration from TDS Sensor Data

The measured trajectory data are smoothed to remove outliers using a simple moving average. The derived speed and acceleration curves are again

smoothed. The resulting distribution of speed and acceleration of the individual segments are shown in Fig. 5. The majority of the speeds are located in the 0~25 km/h range. This is explained by the fact that, typically, only the first few vehicles after the green light have been annotated to achieve results for the most significant phase with respect to emissions. The acceleration values calculated for the corresponding segments have a maximum of their distribution in the range of 1~2 m/s^2 . Higher values up to 5 m/s^2 can be seen in Fig. 5, however these results are most probably from a few outliers that have not been removed by the smoothing step. More advanced filtering algorithms may be required. The published results of Hirschmann et al. [5], Rakha et al. [7] and Wang [8] suggest that acceleration values for stop line accelerations are in the 1~2 m/s^2 range with peak accelerations which are in the 3~4 m/s^2 range. Our results support the findings with a slightly higher peak acceleration observed.

Fig. 6 shows the obtained field data as a scatter plot of speed-acceleration pairs, with each dot representing the result from an individual trajectory segment. Although the scatter plot suggests accelerations up to 5 m/s^2 , the distribution density shows that this is only true for very few segments indicating that these are outliers.

5.2 Comparison with Traffic Micro Simulation

The comparison between micro simulation and TDS acceleration distributions is shown in Fig. 6. This analysis suggests that there are inconsistencies between measured distributions of real-world acceleration behavior and ones observed in the traffic micro simulation model. As can be seen from the speed and acceleration plots in Fig. 6, the acceleration values at lower speed (below 10 km/h) are much more spread in reality than in simulation. In the simulation results, the acceleration is quite uniformly distributed over a straight line at lower speed, with little variation observed. In contrast, the field data suggest that there is substantial variation, with a much broader distribution than in simulation.

A plausible explanation for this is that, in reality, due to heterogeneity in driver behavior, drivers accelerate from stop line in a more varied fashion than in the simulations. This is consistent with the findings of Wilmink et al. [4].

Table 1 Micro simulation settings.

Vehicle type	Fleet composition (%)	Desired speed (km/h)	Desired acceleration (m/s^2)
Cars	98	50	3.5
HGV	2	30	2.5

Fig. 5 Distributions of all trajectory segments derived for the cars accelerating from the stop line derived from the manual trajectory annotation: (a) Speed; and (b) acceleration.

Field data

Microsimulation results

Fig. 6 (a) Field data scatter plot of acceleration and speed; (b) field data distribution density plot; (c) micro simulation data scatter plot of acceleration and speed; (d) micro simulation data distribution density plot.

A further observation is that the rate of acceleration in the simulation (below the speed of 2 km/h) tends to be higher than in reality, with the majority of simulated vehicles having an acceleration from the stop line that corresponds to the upper bounds of the observed distribution. In reality, the majority of vehicles have lower acceleration values. This is clearly illustrated in the density distribution graph in Fig. 6.

In the context of emissions estimation, the consequence of this hard acceleration behavior in micro simulation will tend to result in an overestimation of emissions for the initial acceleration phase at this location. Therefore, it is crucial to calibrate these default simulation parameters to make it closer to real-world vehicle acceleration trajectory in order to obtain realistic emission estimate for a specific test site.

6. Conclusions

This study investigated the acceleration behavior of passenger cars at the stop line of a traffic light in an urban area. A comparison of vehicle acceleration distributions obtained from an optical smart eye TDS traffic sensor and a micro simulation tool has been undertaken. The results obtained from the sensor in a speed range from 0 to 40 km/h show the majority of acceleration values in the range of 1–2 m/s^2 . A comparison with the results from the traffic micro simulation software shows that the measured acceleration, especially in the speed range below 10 km/h, is distributed more widely than in the simulation results, and with generally lower acceleration rates. This analysis suggests that the default acceleration

distribution in the micro simulation tool should be replaced by measured data to ensure accurate representation of driver behavior. This is particularly relevant when traffic micro simulation tools are used in conjunction with emission models as acceleration distribution greatly affects emission estimates.

The optical sensor system developed here for the recording of vehicle trajectories is significantly more flexible and easier to integrate in roadside infrastructure than the video-based measurement systems described in the literature. The embedded sensor offers the possibility to implement the acceleration sensing directly in the device serving as a smart traffic sensor that allows future traffic management systems to ingest live acceleration data from the road network, and infer local estimations of traffic behavior and emissions.

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