Online Driving Behavior Scoring using Wheel Speeds

Marian Waltereit[a], Peter Zdankin, Viktor Matkovic, Maximilian Uphoff and Torben Weis[b]
Distributed Systems Group, University of Duisburg-Essen, 47048 Duisburg, Germany

Keywords: Driving Behavior, Aggressive Driving, Driver Feedback, Wheel Speeds, Controller Area Network.

Abstract: We present an online scoring algorithm for measuring driving behavior using wheel speeds only. Such an algorithm can be used to provide drivers with feedback about their driving behavior while driving in order to reduce aggressive driving, which is a primary cause of traffic accidents. Our algorithm uses a minimal data set already available through the built-in wheel speed sensors of contemporary cars. Due to the small amount of data used and the low computational complexity, our algorithm can easily be deployed on single-board computers. With real driving experiments in a controlled and an uncontrolled environment, we demonstrate the suitability of our scoring algorithm for identifying aggressive driving and assessing the driving behavior.

1 INTRODUCTION

Vehicular accidents are often caused by aggressive driving behavior, such as extreme acceleration or deceleration (Luo Yong and Li Hui, 2009; Paleti et al., 2010; Ma et al., 2019). The risk such accidents could be reduced by giving drivers feedback on their driving behavior. Without feedback, drivers can typically only monitor the velocities of their cars to assess whether they are within legal limits. Other physical quantities such as the car's acceleration are difficult to grasp while driving without further assistance. However, the acceleration of the car is another indicator of the quality of the driving behavior, since a moderate and steady acceleration implies a safer driving style that endangers other drivers less. A behavioral score, on the other hand, can be understood more intuitively and is less of a cognitive burden for drivers. Such a score can be calculated using physical quantities from in-vehicle data of contemporary cars and indicates either non-aggressive or aggressive driving behavior. If drivers check their scores regularly, they are able to notice reductions and adjust their behavior towards a non-aggressive driving style to raise the score back to a good rating. Moreover, the awareness of the individual driving behavior can be improved.

Our contribution is an online scoring algorithm for measuring driving behavior using wheel speeds only. An online algorithm rates the driving behavior while driving. In contrast, offline algorithms rate the driving behavior retrospectively after the trip. Due to the mandatory anti-lock braking system (ABS), wheel speeds can be obtained from built-in wheel speed sensors of contemporary cars via the Controller Area Network (CAN bus) (Reif, 2011). As a result, our scoring algorithm can potentially be used in a large number of today's cars. We identify wheel speeds as the minimal data set adequate and required for the purpose of driving behavior scoring. Thus, our algorithm follows the principle of data minimization as defined in the EU General Data Protection Regulation (GDPR) (Council of the European Union and European Parliament, 2016). The small amount of data used and the low computational complexity make our algorithm easy to deploy on single-board computers.

The rest of this paper is organized as follows. We first discuss related approaches for measuring driving behavior in Section 2. In Sections 3 and 4, we describe the system model and introduce the kinematic car data used in our paper. We present our scoring algorithm in Section 5. In Section 6, we evaluate our scoring algorithm with real driving experiments in a controlled and an uncontrolled environment. Finally, we conclude the paper in Section 7.

2 RELATED WORK

In behavioral science, the definition of aggressive driving is manifold. As Dula et al. (Dula and Geller, 2003) point out, the term is used in different contexts. In psychology, the term is used to refer to three types

[a] https://orcid.org/0000-0001-5480-8783
[b] https://orcid.org/0000-0001-6594-326X

Waltereit, M., Zdankin, P., Matkovic, V., Uphoff, M. and Weis, T.
Online Driving Behavior Scoring using Wheel Speeds.
DOI: 10.5220/0009215604170424
In *Proceedings of the 6th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2020)*, pages 417-424
ISBN: 978-989-758-419-0

of aggressive driving behavior: 1) acts of bodily or psychological aggression towards other road users, 2) negative emotions while driving, and 3) risk-taking driving behavior without intent to harm other road users. In this paper, we refer to the third type of driving behavior since it is a measurable behavior that is reflected in in-vehicle data from the CAN bus. Examples for the third driving behavior type are weaving in and out of traffic, speeding or changing speed unpredictably (James, 2009).

Several approaches for measuring driving behavior have already been proposed. The methodology used include questionnaires, fuzzy logic and machine learning (Imkamon et al., 2008; Castignani et al., 2015; Ma et al., 2019; Carfora et al., 2019). In the following, we focus on scoring-based approaches, as these are most related to our work.

Castignani et al. (Castignani et al., 2015) proposed a smartphone-based driver profile platform. While they use accelerometer, magnetometer and gravity sensor readings as well as GPS data to detect driving events first, information about the weather and time of day is used to calculate a score based on the events. The detection of driving events is based on a fuzzy inference system. However, due to the use of smartphones, their approach requires a calibration phase based on statistical analysis to determine the thresholds for the fuzzy inference system. We use an adaptive threshold that is based on physical limitations of car dynamics and does not require a calibration phase.

Bergasa et al. (Bergasa et al., 2014) developed an app for smartphones to warn inattentive drivers while evaluating and scoring driving behavior. They use a variety of sensors and integrated hardware such as camera, microphone, GPS and inertial sensors. The resulting data is used to calculate two types of scores. The first score describes the drowsiness of the driver, which is calculated from the camera shots using image processing. The second score represents and rates the distraction of the driver using inertial sensors. However, the smartphone is used as a fixed vehicle-mounted device, i.e. the axis of the smartphone's acceleration and gyroscope sensors must be aligned with the corresponding axis of the car. Such a setup is susceptible to operating errors and external influences, which can lead to undesirable problems such as incorrect scoring. In contrast to our approach, they use fixed thresholds for detecting and rating driving events. In addition, we use in-vehicle data and do not require inertial sensors of a smartphone.

Eboli et al. (Eboli et al., 2016) proposed a methodology to analyze driving behavior using velocity as well as longitudinal and lateral accelerations obtained from a smartphone with GPS to distinguish safe from unsafe driving behavior. Then, they extended the methodology by incorporating vertical acceleration (Eboli et al., 2019). In contrast to the in-vehicle data used in our work, GPS is not always available, e.g. in tunnels. Nevertheless, in our scoring algorithm we utilize the safety threshold introduced by Eboli et al. (Eboli et al., 2016), which is based on physical limitations of car dynamics.

Carfora et al. (Carfora et al., 2019) proposed an approach to characterize driving behavior using unsupervised classification algorithms such as k-means. They calculate aggressiveness indices that are used to derive a risk index. For this, they use a total of 10 features from CAN bus and GPS sensor readings, e.g. engine revolutions per minute (RPM) and acceleration. The GPS-based features are used to determine the type of road and the time at which the car was driven. Yet again, the problem is that GPS is not always available.

Abdelrahman et al. (Abdelrahman et al., 2018) presented a data-driven approach that uses machine learning algorithms to predict a driver's accident risk probability. They calculate the risk probability on the basis of 12 driving behavior features, such as sudden braking, already included in the naturalistic driving data set used. Based on the risk prediction they calculate a final driver's risk score. However, not all of the features used can be obtained from in-vehicle data and require external information such as speed limits.

In contrast to our approach, most of the aforementioned existing approaches require data from various sensors for measuring driving behavior. Our objective is to provide a scoring algorithm with a low computational complexity that uses only a minimal data set obtained from the car's CAN bus. Hence, our algorithm follows the principle of data minimization as defined in the GDPR (Council of the European Union and European Parliament, 2016).

In above context, Kar et al. (Kar et al., 2019) proposed a scoring algorithm that uses gyroscope and RPM readings as the minimal data set for scoring driving behavior. This data is available in all car models through the on-board diagnostics port. However, the data set used is less minimal than in our approach. Using time series forecasting methods, they predict future gyroscope and RPM values in order to identify anomalies, i.e. changes in driving behavior. Finally, they calculate a score based on the prediction errors.

3 SYSTEM MODEL

We assume a system with the following four components: a driver, a car, a scoring device, and a display. The driver drives a car equipped with a scoring device. This scoring device is capable of calculating a driving behavior score using wheel speeds only. As a result, external information such as traffic conditions or speed limits are not required. The scoring device is connected to the car's high speed CAN bus and waits for wheel speed messages broadcasted over the CAN bus. Using methods as introduced by Marchetti et al. (Marchetti and Stabili, 2019), the identifier of wheel speed messages can be automatically identified. This is useful, as this information is not standardized for private transport and usually not published by manufacturers. Using wheel speeds, the scoring device calculates and updates the driver's score while driving. A display is connected to the scoring device and displays the score in order to give the driver feedback about his or her driving behavior. Based on the feedback, the driver is able to improve his or her driving behavior in order to avoid accidents.

4 KINEMATIC CAR DATA

We utilize time-stamped wheel speeds from the car's CAN bus to calculate the kinematic car data. We denote the right and left front wheel speeds as $w_{\mathrm{rf}}(t)$ and $w_{\mathrm{lf}}(t)$. Accordingly, $w_{\mathrm{rr}}(t)$ and $w_{\mathrm{lr}}(t)$ represent the speeds of the right and left rear wheels. We denote a wheel speed measurement $\mathcal{W}(t)$ at time t as:

$$\mathcal{W}(t) = (w_{\mathrm{rf}}(t), w_{\mathrm{lf}}(t), w_{\mathrm{rr}}(t), w_{\mathrm{lr}}(t)), \tag{1}$$

where the wheel speeds are in $\mathrm{m\,s^{-1}}$.

We estimate the car's velocity $v(t)$ at time t by the mean of the right and left rear wheel speeds $w_{\mathrm{rr}}(t)$ and $w_{\mathrm{lr}}(t)$ (Carlson et al., 2002):

$$v(t) = \frac{w_{\mathrm{rr}}(t) + w_{\mathrm{lr}}(t)}{2} \tag{2}$$

We estimate the yaw rate $r(t)$ of a car at time t using the car's rear track width $\mathcal{T}$ and the right and left rear wheel speeds $w_{\mathrm{rr}}(t)$ and $w_{\mathrm{lr}}(t)$ (Carlson et al., 2002):

$$r(t) = \frac{w_{\mathrm{rr}}(t) - w_{\mathrm{lr}}(t)}{\mathcal{T}} \tag{3}$$

The first derivative of the velocity $v(t)$ is the longitudinal acceleration $a_{\mathrm{lon}}(t)$. We estimate the car's lateral acceleration $a_{\mathrm{lat}}(t)$ using the velocity $v(t)$ and the yaw rate $r(t)$, neglecting the sideslip angle (Chen et al., 2016):

$$a_{\mathrm{lat}}(t) = v(t) \cdot r(t) \tag{4}$$

The acceleration vector $a(t)$ includes the longitudinal and the lateral acceleration at time t as:

$$a(t) = (a_{\mathrm{lon}}(t), a_{\mathrm{lat}}(t)) \tag{5}$$

We calculate the orientation-independent total acceleration $\|a(t)\|$ as the magnitude of the acceleration vector $a(t)$:

$$\|a(t)\| = \sqrt{a_{\mathrm{lon}}(t)^2 + a_{\mathrm{lat}}(t)^2} \tag{6}$$

5 SCORING ALGORITHM

We introduce a driving behavior score between 0 and 100 points. A score of 0 points indicates that the driving behavior is consistently aggressive and a score of 100 points indicates that the driving behavior is consistently non-aggressive. This way the driving behavior can be monitored throughout the trip and drivers can receive feedback on their respective driving behavior. In order to calculate the score, we use wheel speeds which are typically available at 100 Hz on the car's CAN bus. However, the frequency may vary depending on the manufacturer. In this case, we resample the wheel speeds to 100 Hz.

For our scoring algorithm, we choose a window-based approach. Based on our experiments, we use non-overlapping windows ω_i with a window size of 1 s. However, if the average velocity of a window is less than $5\,\mathrm{km\,h^{-1}}$, we discard that window because the car is idling or barely moving. For each window, we calculate a window score based on the driver's current driving behavior. Each window score contributes to the overall driving behavior score.

For each non-overlapping window ω_i, we calculate the car's total acceleration $\|a(t)\|$ (see Equation (6)). The total acceleration includes both driving straight ahead and turning, as it is made up of longitudinal and lateral acceleration. As a result, the total acceleration is particularly suitable for measuring driving behavior, since accelerations, decelerations and turnings are sufficient to represent all types of driving maneuvers (Van Ly et al., 2013).

To measure driving behavior based on the total acceleration $\|a(t)\|$, we leverage a safety threshold (denoted as θ_t) that is based on the physical limitations of car dynamics and was introduced by Eboli et al. (Eboli et al., 2016). The safety threshold θ_t (in $\mathrm{m\,s^{-2}}$) is calculated using the car's velocity $v(t)$ (in $\mathrm{km\,h^{-1}}$):

$$\theta_t = g \cdot \left[0.198 \cdot \left(\frac{v(t)}{100} \right)^2 - 0.592 \cdot \frac{v(t)}{100} + 0.569 \right], \tag{7}$$

where g is the gravitational acceleration on Earth and $v(t) \leq 150\,\mathrm{km\,h^{-1}}$. The safety threshold value is defined for velocities up to $150\,\mathrm{km\,h^{-1}}$ (Eboli et al., 2016). Hence, we use the safety threshold of $150\,\mathrm{km\,h^{-1}}$ for velocities greater than $150\,\mathrm{km\,h^{-1}}$.

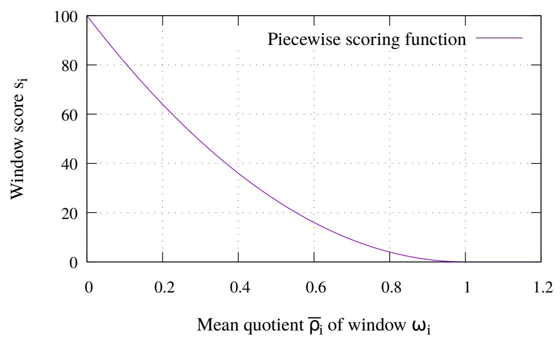

Figure 1: Piecewise scoring function used in this paper for calculating the window score.

The safety threshold θ_t defines a safety domain in which the total acceleration $\|a(t)\|$ is considered safe, i.e. it is physically safe to drive the car under these conditions (Eboli et al., 2016):

$$\|a(t)\| < \theta_t \tag{8}$$

If the total acceleration $\|a(t)\|$ exceeds the safety threshold θ_t, driving is considered unsafe. In general, an unsafe driving situation is due to aggressive driving (Eboli et al., 2016).

For each time step t of the window ω_i, we calculate the quotient of total acceleration $\|a(t)\|$ and safety threshold θ_t (denoted as ρ_t):

$$\rho_t = \frac{\|a(t)\|}{\theta_t} \tag{9}$$

The quotient ρ_t indicates how close the driving behavior is to a physically unsafe driving situation at time step t. The arithmetic mean of all quotients ρ_t of the window ω_i is denoted as $\overline{\rho_i}$.

We use the mean quotient $\overline{\rho_i}$ of the window ω_i for calculating the window score $s_i \in [0,100]$ that indicates the current driving behavior. In detail, we calculate the window score $s_i \in [0,100]$ by the following piecewise function (referred to as *scoring function*):

$$s_i = \begin{cases} 100 \cdot (\overline{\rho_i} - 1)^2 & 0 \leq \overline{\rho_i} < 1 \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

The scoring function is depicted in Figure 1. This scoring function allows to account for the closeness of the driving behavior within the window to a physically unsafe driving situation. If the driving behavior is most safe (i.e. least aggressive), the window score is close to 100 points. In turn, the window score is close to 0 points if the driving behavior is most unsafe (i.e. most aggressive). The less aggressive the driving behavior, the faster the score increases. This should motivate drivers to drive less aggressive.

As mentioned before, each window score contributes to the overall driving behavior score. We calculate the overall driving behavior score $\overline{s_t} \in [0,100]$ at time t as the arithmetic mean of all window scores $s_1,\ldots,s_i$ calculated up to time t:

$$\overline{s_t} = \frac{1}{i}\sum_{j=1}^{i} s_j \tag{11}$$

By using the mean of the window scores, we consider the behavioral history of a driver throughout the entire trip. This leads to a fair score, as drivers who have driven non-aggressive for a long time do not risk their good scores immediately if they drive aggressive for a short term. Vice versa, this also applies to aggressive drivers who drive non-aggressive in the short term.

6 EVALUATION

In order to evaluate our online scoring algorithm, we first conduct a driving experiment in a controlled environment at our university. Then, we use a freely available data set (Kwak et al., 2016) recorded in a driving experiment with five drivers in Seoul to evaluate our algorithm in an uncontrolled environment.

6.1 Controlled Environment

In this section, we examine whether our scoring algorithm can identify aggressive driving behavior. For this, we conduct a driving experiment in a controlled environment where the drivers complete a test course under time pressure. In general, hurried drivers tend to drive more aggressively (Fitzpatrick et al., 2017). Thus, we expect a driver's score to be lower when the driver is under time pressure. If this is the case, our scoring algorithm can identify aggressive driving behavior. Below, we first describe the setup of our driving experiment. Then, we present and discuss the results.

6.1.1 Experimental Setup

In order to examine whether the driving behavior score is lower when driving under time pressure, we set up a test course on the university parking lot. The test course is visualized in Figure 2 and measures about 350 m. On this test course, the drivers have to drive twice through a slalom course and have to make a change of direction once.

A total of five drivers participate in this experiment at daytime in rainy weather conditions. Each driver drives the test course three times. There is no time limit for the first trip and the drivers are instructed to drive in a manner appropriate to themselves. However, the time needed to complete the first trip is measured. Based on this time, a time limit

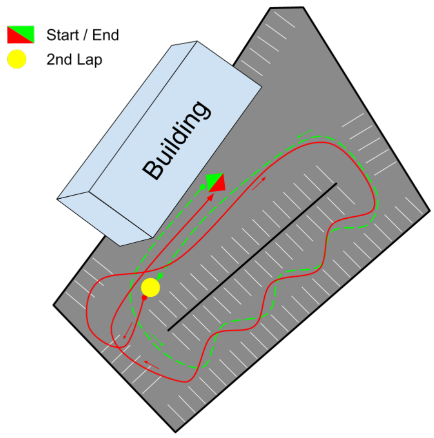

Figure 2: Test course on the university parking lot including two slalom sections and a change of direction.

is set for the two following trips. The time limit of the second trip is 90% of the measured time. For the third trip, the time limit is 75% of the measured time. The drivers are instructed to complete the test course within the respective time limits. During the second and the third trip, the drivers are informed about the remaining time. However, the driving behavior score is not displayed to the drivers in any of the three trips in order to avoid influencing the driving behavior.

Throughout the experiment, a Raspberry Pi 2 equipped with a PiCAN2 board[1] is connected to the car's high speed CAN bus. To ensure a reproducible experimental setup, we record the entire CAN bus data while driving and replay the CAN log file to a virtual CAN interface on the Raspberry Pi 2 afterwards. We prototyped our scoring algorithm in Python and all calculations are performed on a Raspberry Pi 2 while replaying the CAN log file.

6.1.2 Results

Table 1 summarizes the results of our driving experiment in a controlled environment. For each trip of each driver, the table shows the measured time, the time limit, the overall driving behavior score at the end of the trip (see Equation (11)). Furthermore, the table provides the arithmetic mean of the overall driving behavior scores weighted by the measured times for each driver.

All drivers reduce their driving times from the first to the second and from the second to the third trip while keeping to the time limits. The average driving time for the first trips is 74 s. For the second and third trip, the average driving time reduces to 56 s and 50 s

[1]http://skpang.co.uk/catalog/pican2-canbus-board-for-raspberry-pi-23-p-1475.html (accessed November 29, 2019)

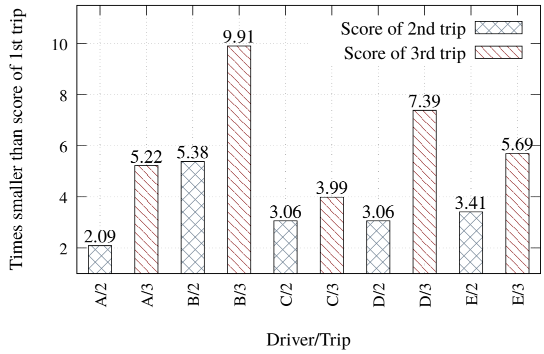

Figure 3: Visualization of the change in driving behavior during the second and third trip of each driver, i.e. how many times the scores of the second and third trips are smaller compared to the driver's score of the first trip.

respectively. Based on the first trip, we determine the time limits for the subsequent trips. The time limits range from 56 s to 75 s for the second and 47 s to 62 s for the third trip.

As there is no time limit for the first trip and the drivers are instructed to drive in a manner appropriate to themselves, we can use the overall driving behavior score of the first trip as a baseline to measure the individual change in driving behavior in the second and third trip for each driver. For this, we determine how many times the overall driving behavior scores of the second and third trips are smaller than the score of the first trip. Figure 3 illustrates the individual change in driving behavior of each driver. The respective overall driving behavior scores of each driver are given in Table 1. The individual driving behavior of driver B changes the most in both trips towards an aggressive driving style compared to all other drivers. The driving behavior scores of driver B's second and third trip (3.74 and 2.03 points) are 5.38 and 9.91 times smaller than driver B's baseline score (20.12 points). In the second trip, driver A's driving behavior changes least compared to the other drivers, i.e. by a factor of 2.09 from 11.5 to 3.37 points. For driver C, the individual driving behavior changes similarly in the second and third trip. The driving behavior score decreases by a factor of 3.06 from 31.06 points to 10.16 in driver C's second trip. In the third trip, the driving behavior of driver C changes by a factor of 3.99 from 31.06 to 7.79 points. Hence, driver C's driving behavior is almost constant during the second and third trip.

In addition to the individual change in the driving behavior, we also compare the driving behavior of the drivers with each other. For this, we use the weighted means of the overall driving behavior scores given in Table 1. In terms of aggressive and unsafe driving, driver E has the worst driving behavior in all three trips with a weighted mean score of 6.18

Table 1: Results of our experiment in a controlled environment. For each driver, the table shows the measured times, the time limits, the overall driving behavior scores at the end of each trip and the arithmetic mean of the driver's scores weighted by the measured times.

Driver	Measured time			Time limit		Overall driving behavior score			Weighted mean score
	1st trip	2nd trip	3rd trip	2nd trip	3rd trip	1st trip	2nd trip	3rd trip	
A	83 s	67 s	56 s	75 s	62 s	32.26	15.47	6.18	19.71
B	69 s	50 s	47 s	62 s	52 s	20.12	3.74	2.03	10.06
C	80 s	55 s	52 s	72 s	60 s	31.06	10.16	7.79	18.44
D	77 s	55 s	50 s	69 s	58 s	32.39	10.57	4.38	18.1
E	62 s	51 s	45 s	56 s	47 s	11.5	3.37	2.02	6.18

points, followed by driver B with a weighted mean score of 10.06 points. Drivers C and D have a comparable aggressive driving behavior with weighted mean scores of 18.44 and 18.1 points respectively. Overall, driver A's driving behavior is the least aggressive with a weighted mean score of 19.71 points.

In summary, the driving behavior scores decrease with decreasing time limits for all drivers. Thus, a lower score reflects a more aggressive driving behavior, as driving behavior tends to be more aggressive under time pressure (Fitzpatrick et al., 2017). This shows that our scoring algorithm is able to identify aggressive driving.

6.2 Uncontrolled Environment

In this section, we evaluate whether our scoring algorithm correctly assesses driving behavior in an uncontrolled environment, i.e. when the drivers were not instructed by us and the trips were performed independently of our work. In particular, we compare our online scoring algorithm with an offline clustering approach to examine whether our algorithm yields similar results. Below, we describe the experimental setup and present the results.

6.2.1 Experimental Setup

We use wheel speeds from a freely available data set recorded in a driving experiment with five drivers in Seoul (Kwak et al., 2016). Each driver completed four comparable trips (about 5.5 km each) in an urban area, resulting in a total of 20 trips. The wheel speeds were recorded at 1 Hz during driving. We resample the wheel speeds to 100 Hz by linear interpolation and calculate the kinematic car data as described in Section 4. However, for one of the trips no wheel speed data was recorded, thus we can only use 19 of the trips in our evaluation.

6.2.2 k-Means Clustering

The freely available data set does not contain any information about the driving behavior of the drivers during the trips. However, clustering algorithms are well established to group drivers and their trips according to their driving behavior (Mainardi et al., 2018; Fugiglando et al., 2019; Mantouka et al., 2019). Thus, we label the driving behavior of the trips based on k-means clustering, i.e. we group the trips according to their underlying driving characteristics. We use the clustering results to evaluate the results of our online scoring algorithm.

The feature vector of each trip includes a total of 12 statistical features of the trip's acceleration and deceleration events, because these events can characterize driving behavior. For example, aggressive drivers usually accelerate and brake stronger than non-aggressive drivers. An acceleration event is characterized by an increasing velocity. Accordingly, a deceleration event is characterized by a decreasing velocity. We calculate the average and standard deviation of the longitudinal acceleration $a_{\text{lon}}(t)$ and lateral acceleration $a_{\text{lat}}(t)$ for each acceleration event and include the respective averages as features in the trip's feature vector. In addition, we include the average and standard deviation of the car's velocity $v(t)$ of all acceleration events in the trip's feature vector. The same applies to deceleration events.

The silhouette score measures the clustering validity and can be used to find the optimal number of clusters (Rousseeuw, 1987). Based on the silhouette score, we cluster the trips into two clusters. We interpret the cluster centers in terms of driving characteristics and define which cluster represents which kind of driving behavior, i.e. non-aggressive and aggressive. We select the cluster with the higher feature values in the center as aggressive. Then we assign a label to each trip according to its cluster, resulting in 10 non-aggressive and 9 aggressive trips as illustrated in Figure 4.

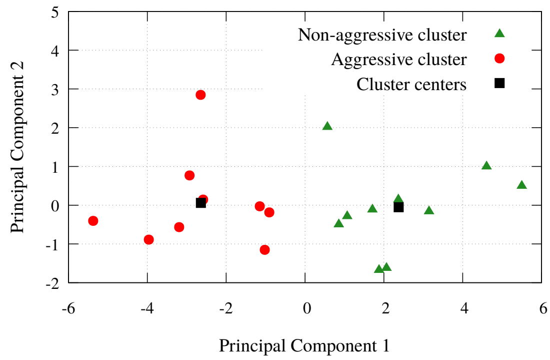

Figure 4: Results of k-means clustering. For visualization, k-means clustering was performed on PCA-reduced data.

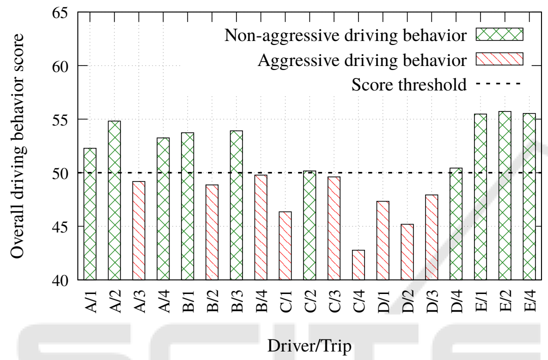

Figure 5: Overall driving behavior score of each trip of each driver for the freely available data set. The bar color/pattern shows the k-means clustering-based driving behavior labels. The dashed black line shows the score threshold for classifying the driving behavior based on our scoring algorithm.

6.2.3 Driving Behavior Score

For each trip, we calculate the overall driving behavior score as defined in Equation (11). Figure 5 shows both the k-means clustering-based labels as well as the calculated driving behavior scores. We choose a score threshold of 50 points to classify the driving behavior as non-aggressive or aggressive. This score threshold divides the scoring range evenly between the two classes of driving behavior considered. A score greater than or equal 50 points is classified as non-aggressive and a score less than 50 points is classified as aggressive.

As Figure 5 shows, we correctly classified the 10 non-aggressive and the 9 aggressive trips. Thus, the score threshold of 50 points provides a good classification performance. In our scoring function defined in Equation (10), the mean quotient $\overline{\rho_i} \approx 0.29$ yields a score of 50 points. Thus, we identify a mean quotient of $\overline{\rho_i} \approx 0.29$ as a good threshold for distinguishing between non-aggressive and aggressive driving behavior.

The results show that our scoring algorithm is suitable for assessing driving behavior in uncontrolled environments, as it performs equally well as the k-means clustering algorithm, i.e. an offline algorithm. In addition, our algorithm does not require data from other trips and works without prior knowledge and is thus of practical use.

7 CONCLUSION

We presented an online scoring algorithm that rates the aggressiveness of a driver. This algorithm can be used to indicate a driver that he or she is taking too much risk. Our approach solely relies on wheel speeds which are available on the CAN bus of contemporary cars. No additional data like GPS, speed limits, traffic- or weather conditions are required. Furthermore, our algorithm can score the driving online while it happens, unlike other approaches that can compare several trips after they are completed.

We first evaluated our scoring algorithm with a driving experiment in a controlled environment, where ground truth was known due to the experimental setup. The results show that our scoring matches the actual driving behavior. In addition, we compared our online scoring algorithm with an offline clustering approach that took a set of comparable trips as input. The results show that our online algorithm performed equally well when compared to the offline algorithm. However, our approach yields a score immediately and does not need a set of comparable trips and not even the entire trip for scoring it. Therefore, our approach is of practical use because it is an online algorithm, has a low computational complexity and requires only a minimal data set, namely the wheel speeds.

Future work should include other physical quantities in addition to the total acceleration in order to improve the measurement of driving behavior. Furthermore, we suggest to compare the presented scoring algorithm with other existing algorithms. For this, however, a suitable data set must be collected, since to the best of our knowledge no such data set exists. We did not study the influence of displaying the score on the driver's driving behavior and leave it for future work.

ACKNOWLEDGEMENTS

We thank the Chair of Mechatronics of the University of Duisburg-Essen and in particular Dieter Schramm for providing the Ford C-Max for our driving experiment.

REFERENCES

Abdelrahman, A., Hassanein, H. S., and Abu-Ali, N. (2018). Data-driven robust scoring approach for driver profiling applications. In *2018 IEEE Global Communications Conference (GLOBECOM)*, pages 1–6.

Bergasa, L. M., Almería, D., Almazán, J., Yebes, J. J., and Arroyo, R. (2014). Drivesafe: An app for alerting inattentive drivers and scoring driving behaviors. In *2014 IEEE Intelligent Vehicles Symposium Proceedings*, pages 240–245.

Carfora, M. F., Martinelli, F., Mercaldo, F., Nardone, V., Orlando, A., Santone, A., and Vaglini, G. (2019). A ”pay-how-you-drive” car insurance approach through cluster analysis. *Soft Comput.*, 23(9):2863–2875.

Carlson, C. R., Gerdes, J. C., and Powell, J. D. (2002). Practical position and yaw rate estimation with gps and differential wheelspeeds. In *Proceedings of AVEC 2002 6th International Symposium of Advanced Vehicle Control*.

Castignani, G., Derrmann, T., Frank, R., and Engel, T. (2015). Driver behavior profiling using smartphones: A low-cost platform for driver monitoring. *IEEE Intelligent Transportation Systems Magazine*, 7(1):91–102.

Chen, W., Xiao, H., Wang, Q., Zhao, L., and Zhu, M. (2016). *Integrated Vehicle Dynamics and Control*. John Wiley & Sons Singapore Pte. Ltd.

Council of the European Union and European Parliament (2016). Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation). *OJ*, L 119:1–88.

Dula, C. S. and Geller, E. (2003). Risky, aggressive, or emotional driving: Addressing the need for consistent communication in research. *Journal of Safety Research*, 34(5):559 – 566.

Eboli, L., Mazzulla, G., and Pungillo, G. (2016). Combining speed and acceleration to define car users' safe or unsafe driving behaviour. *Transportation Research Part C: Emerging Technologies*, 68:113 – 125.

Eboli, L., Mazzulla, G., and Pungillo, G. (2019). Incorporating vertical acceleration for defining driving behaviour. *International Journal of Information Retrieval Research*, 9(2):38–48.

Fitzpatrick, C. D., Samuel, S., and Knodler, M. A. (2017). The use of a driving simulator to determine how time pressures impact driver aggressiveness. *Accident Analysis & Prevention*, 108:131 – 138.

Fugiglando, U., Massaro, E., Santi, P., Milardo, S., Abida, K., Stahlmann, R., Netter, F., and Ratti, C. (2019). Driving behavior analysis through can bus data in an uncontrolled environment. *IEEE Transactions on Intelligent Transportation Systems*, 20(2):737–748.

Imkamon, T., Saensom, P., Tangamchit, P., and Pongpaibool, P. (2008). Detection of hazardous driving behavior using fuzzy logic. In *2008 5th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology*, volume 2, pages 657–660.

James, L. (2009). *Road Rage and Aggressive Driving: Steering Clear of Highway Warfare*. Prometheus Books.

Kar, G., Asiroglu, B., and Bir, F. S. (2019). Scotto: Real-time driver behavior scoring using in-vehicle data. In *2019 IEEE 89th Vehicular Technology Conference (VTC2019-Spring)*, pages 1–5.

Kwak, B. I., Woo, J., and Kim, H. K. (2016). Know your master: Driver profiling-based anti-theft method. In *2016 14th Annual Conference on Privacy, Security and Trust (PST)*, pages 211–218.

Luo Yong and Li Hui (2009). The analysis of the aggressive driving for the traffic safety. In *2009 International Conference on Industrial Mechatronics and Automation*, pages 117–120.

Ma, Y., Zhang, Z., Chen, S., Yu, Y., and Tang, K. (2019). A comparative study of aggressive driving behavior recognition algorithms based on vehicle motion data. *IEEE Access*, 7:8028–8038.

Mainardi, N., Zanella, M., Reghenzani, F., Raspa, N., and Brandolese, C. (2018). An unsupervised approach for automotive driver identification. In *Proceedings of the Workshop on INTelligent Embedded Systems Architectures and Applications*, INTESA '18, pages 51–52, New York, NY, USA. ACM.

Mantouka, E. G., Barmpounakis, E. N., and Vlahogianni, E. I. (2019). Identifying driving safety profiles from smartphone data using unsupervised learning. *Safety Science*, 119:84 – 90.

Marchetti, M. and Stabili, D. (2019). Read: Reverse engineering of automotive data frames. *IEEE Transactions on Information Forensics and Security*, 14(4):1083–1097.

Paleti, R., Eluru, N., and Bhat, C. R. (2010). Examining the influence of aggressive driving behavior on driver injury severity in traffic crashes. *Accident Analysis & Prevention*, 42(6):1839–1854.

Reif, K., editor (2011). *Bosch Autoelektrik und Autoelektronik*. Vieweg+Teubner Verlag.

Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*, 20:53 – 65.

Van Ly, M., Martin, S., and Trivedi, M. M. (2013). Driver classification and driving style recognition using inertial sensors. In *2013 IEEE Intelligent Vehicles Symposium (IV)*, pages 1040–1045.