Driver Evaluation in Heavy Duty Vehicles Based on Acceleration and Braking Behaviors

Mehmet Emin Mumcuoglu, Gokhan Alcan, Mustafa Unel
Faculty of Engineering and Natural Sciences
Sabanci University
Istanbul, Turkey
munel@sabanciuniv.edu

Onur Cicek, Mehmet Mutluergil,
Metin Yilmaz, Kerem Koprubasi
Product Development
Ford OTOSAN
Istanbul, Turkey

***Abstract*—In this paper, we present a real-time driver evaluation system for heavy-duty vehicles by focusing on the classification of risky acceleration and braking behaviors. We utilize an improved version of our previous Long Short Memory (LSTM) based acceleration behavior model [10] to evaluate varying acceleration behaviors of a truck driver in small time periods. This model continuously classifies a driver as one of six driver classes with specified longitudinal-lateral aggression levels, using driving signals as time-series inputs. The driver gets acceleration score updates based on assigned classes and the geometry of driven road sections. To evaluate the braking behaviors of a truck driver, we propose a braking behavior model, which uses a novel approach to analyze deceleration patterns formed during brake operations. The braking score of a driver is updated for each brake event based on the pattern, magnitude, and frequency evaluations. The proposed driver evaluation system has achieved significant results in both the classification and evaluation of acceleration and braking behaviors.**

***Index Terms*—Driver evaluation, driver behaviors, classification, LSTM networks, heavy-duty vehicles, acceleration, braking**

I. Introduction

Driving and road safety have been one of the major concerns of the automotive industry. Continuous efforts have been made in the development of safety-improving vehicle systems. For instance, in the last decade, Advanced Driver Assistance Systems (ADAS) have become greatly popular, aiming to enhance vehicle safety by assisting drivers using the real-time risk analysis [1]. Despite improving technologies in modern vehicles, the main cause of the majority of lethal traffic accidents is incorrect driving behaviors [2]. Therefore, it is essential to identify various driving behaviors and evaluate their risk in real-time to maximize vehicle safety, especially for heavy-duty vehicles [3].

In the literature, numerous methods have been proposed for the classification and evaluation of driving behaviors. These methods can be grouped as driver state-based and vehicle dynamics-based methods. Driver state-based methods are designed to identify risky driving states, e.g. fatigue, drunk, and drowsy by monitoring drivers by using visual features obtained from active sensors [4]. On the other hand, vehicle dynamics-based methods are designed to classify driving behaviors using driving signals, such as vehicle-engine speeds, longitudinal-lateral accelerations, accelerator-brake pedal positions, etc.. These signals can be obtained from the vehicle's onboard sensors [5], [7], [9], [10] or external measurement devices [6]. To classify driving behaviors, Saleh et al. [6] designed a vehicle dynamics-based approach, using recurrent neural networks (RNN). Imamura et al. [7] developed a driving behavior classification method for the evaluation of abnormal steering behaviors. Naito et al, [8] evaluate drivers based on rapid brake behaviors with a clustering analysis. Miyajima et al., [9] proposed a method to evaluate acceleration, rapid deceleration, and steering behaviors of drivers.

In this paper, we propose a system to enhance the safety of heavy-duty vehicles by evaluating the acceleration and braking behaviors of drivers in real-time. For the evaluation of acceleration behaviors, truck drivers are categorized into six classes, based on their longitudinal and lateral acceleration behaviors. Acceleration behaviors of a driver are evaluated for every 30-seconds sample of driving, based on the assigned class and the road geometry in that time interval. The specified driver classes are designed to represent different driving characteristics of real drivers. In order to recognize these characteristics from real driving sequences, a Long Short Term Memory (LSTM) network is trained with possible driving scenarios of defined drivers. The LSTM network is a Recurrent Neural Network (RNN) structure that is chosen for the acceleration behavior model due to its capability of capturing long-term dependencies in time series signals. Driving scenarios to train/test the models are generated in TruckMaker vehicle-dynamics simulation software. For the evaluation of braking behaviors, the deceleration patterns during brake operations are extracted. For each brake, patterns formed before and after the lowest acceleration point are modeled with a fast line fitting method. Braking behaviors of a driver are evaluated for brake events, using a frequency, magnitude, and pattern analysis.

The remaining of this paper is organized as follows, in Section II, the acceleration behavior model is explained with the design of experiment and LSTM based driver classification algorithm. In section III, the braking behavior model is presented. In section IV, driver evaluation methodologies for developed models are described. Results are discussed in section V and, conclusions are provided in Section VI.

II. Acceleration Behavior Model

The acceleration behavior model is designed to classify truck drivers into specified driver categories. Each driver class represents a different aggression level of a real driver in longitudinal or lateral directions. In this section, an enhanced version of the driving behavior classification model, proposed in [10], is presented with improved driver-road designs and classification methodology.

A. Experiment Design

Speed and acceleration parameters are known to be essential for determining the safety of driving behaviors [11]. Longitudinal and lateral accelerations of a driver, form his/her normal and curve driving characteristics [12]. Therefore, a realistic driver model, with configurable longitudinal - lateral acceleration parameters, is developed to generate driver classes using MATLAB Simulink and TruckMaker simulation environment.

The driver model controls the speed of the truck with throttle and brake inputs, as a real driver, without exceeding user-defined acceleration and speed limits in different road curves. This driver model consists of a target speed generator algorithm, that continuously calculates a target speed based on limit parameters and upcoming road geometry, and a proportional-integral (PI) controller, that generates required throttle and brake outputs.

The research has shown that driver models with the constant maximum acceleration assumption, are not capable of representing the acceleration behaviors sufficiently, because drivers prefer to achieve lower acceleration levels while driving at higher speeds [13]. Therefore, the main modification made in this version of the driver model is moving the target speed generator block to the Simulink to achieve variable acceleration limits. The longitudinal acceleration limit of the driver model is redefined as a linearly decreasing function of speed to improve the acceleration behavior representation and maintain the simplicity of parameter selection. This way of describing the acceleration is named linear decay model [13], which is defined as follows:

$$a_x(t) = a_{xmax} - \frac{a_{xmax}}{v_e} v(t) \tag{1}$$

The longitudinal acceleration limit ($a_x(t)$) reaches to its maximum (a_{xmax}) at the speed of 0 km/h. It drops linearly to 0 until the vehicle speed ($v(t)$) reaches to the equilibrium point (v_e). By noting that $a_x(t) = \dot{v}(t)$, the target speed at that time instant can be calculated by solving (1) as

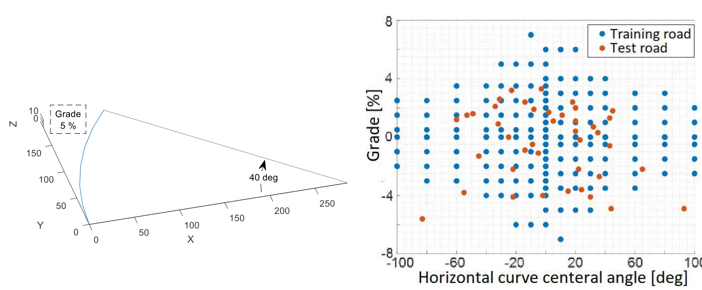
$$v(t) = v_e(1 - e^{-\frac{a_{xmax}}{v_e}t}) + v_0 e^{-\frac{a_{xmax}}{v_e}t} \tag{2}$$

where v_0 is the initial speed of the vehicle. For the ease of representation, the linear-decay acceleration behavior of the driver, defined in (1), is described with two parameters, longitudinal acceleration limit at 0 and 90 km/h. As a result, the proposed driver model has five parameters that are, longitudinal acceleration limit at 0 and 90 km/h (a_{x0},a_{x90}), deceleration limit (a_{xd}), lateral acceleration limits for left and right turns (a_{yl},a_{yr}). Finally, six driver classes are generated with the parameters provided in Table I.

TABLE I
Driver Model Parameters

	Longitudinal Acceleration Limits			Lateral Acceleration Limits	
Driver #	a_{x0} $[m/s^2]$	a_{x90} $[m/s^2]$	a_{xd} $[m/s^2]$	a_{yl} $[m/s^2]$	a_{yr} $[m/s^2]$
1	0.3	0.1	1.0	0.2	0.2
2	0.3	0.1	1.5	0.8	0.8
3	0.3	0.1	2.0	1.4	1.4
4	0.6	0.4	1.0	0.2	0.2
5	0.6	0.4	1.5	0.8	0.8
6	0.6	0.4	2.0	1.4	1.4

In order to observe complete behaviors of generated drivers in simulations, a virtual training road is designed, aiming to imitate all possible vertical and horizontal road curves of a highway. The shape of this road is formed by a number of road blocks, which are 200m length road parts with a constant grade and central angle parameters (Fig. 1a). The grade parameter is defined positive for uphill and negative for downhill roads, while the central angle parameter is defined positive for right-turn, negative for left-turn and zero for straight roads. Complete training road contains many combinations of road shapes in -8,+8% grade, -100,+100°central angle range. A more detailed explanation is provided in [10]. In this paper, the training road design is improved by removing the road blocks with extreme grades and sharp curvatures together, which is not a realistic scenario for real highways. Hence, the length of the final training road is cut to 74.3 km, while the test road remains 8 km long. Grade - horizontal curve central angle coverage plot of modified training and test roads is shown in Fig. 1b.



(a) (b)

Fig. 1. Example road block (a), training and test roads coverage plot (b).

B. Driver Classification

The validity of the acceleration behavior model is established by the generation of comprehensive driving simulations of specified driver categories, and training the system with significant outputs from this driving dataset. Overview of the process of training the acceleration behavior model is presented in Fig. 2.

A physical model of a Ford semitrailer truck is generated in TruckMaker using dimensions, engine and powertrain pa-

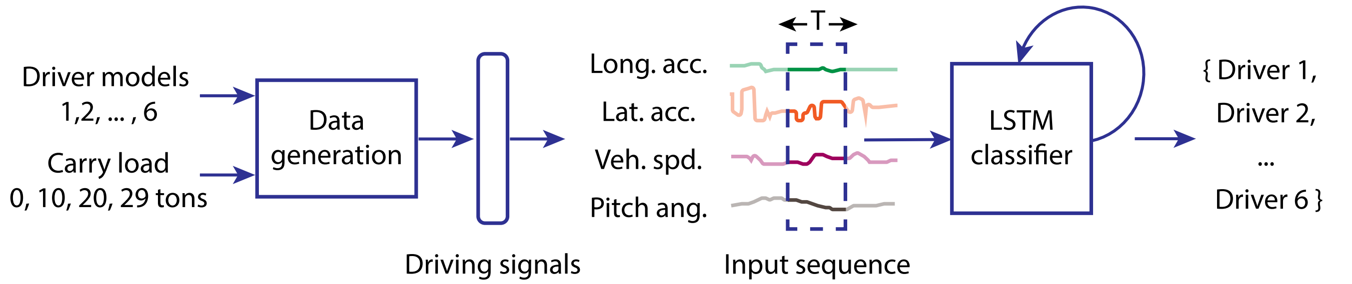


Fig. 2. Training of the acceleration behavior model. Driving data are generated for all driver model - carry load combinations. A many to one LSTM network [15] is utilized for driver classification from selected driving signals in a time window (T). These signals are longitudinal and lateral accelerations, vehicle speed and pitch angle.

rameters, and aerodynamic properties of the real vehicle. The dynamics of a truck change dramatically with widely varying trailer loads, which leads to a significant change in driving behavior as well. For our case, the modeled truck weighs 12.5 tons, while carrying an empty trailer, and 41.5 tons while it is fully loaded (based on its gross towing weight limits). Therefore, all driver models are simulated separately for 0, 10, 20, 19 tons of carry loads in both training and test roads.

The final set has 48 driving simulations with an equal separation between driver, load, and road types. During these simulations, 16 vehicle signals are recorded at 5 Hz which indicate the effect of driving characteristics, and can also be collected from the real truck's inertial measurement unit (IMU), e.g., vehicle speed, longitudinal-lateral accelerations, pedal positions. The complete dataset is divided into 30-second samples with 15-second overlap, and each sample is labeled with the driver id.

It is known that correlated input variables may slow down the learning and affect the accuracy of the network. Thus, linear dependence between vehicle signals is calculated for the proposed algorithm using the Pearson correlation coefficient which is defined for signals A-B as follows,

$$\rho(A,B) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{A_i-\mu_A}{\sigma_A}\right)\left(\frac{B_i-\mu_B}{\sigma_B}\right) \quad (3)$$

where N is the number of data points, μ is mean and σ is standard deviation of the signal.

TABLE II
CORRELATION COEFFICIENTS OF POTENTIAL INPUTS

	Lon. acc.	**Lat. acc.**	**Eng. spd.**	**Veh. spd.**	**Throttle**	**Pitch ang.**
Lon. acc.	1	-0.0002	0.4307	0.0031	0.3934	0.0119
Lat. acc.	-0.0002	1	0.0109	-0.0031	0.0480	0.0862
Eng. spd	0.4307	0.0109	1	0.3642	0.7385	0.3513
Veh. spd.	0.0031	-0.003	0.3642	1	0.3954	-0.0112
Throttle	0.3934	0.0480	0.7385	0.3954	1	0.6327
Pitch ang.	-0.012	-0.0862	-0.3513	0.0112	-0.63274	1

Intuitively, all six inputs from the previous model [10] provide valuable information about driving behaviors independently. However, based on the correlation coefficient matrix (Table II) it is found that the engine speed and throttle signals are not significant for the acceleration behavior model when the longitudinal acceleration and vehicle speed and pitch angle inputs are utilized. As a result, the previous model is simplified by selecting 4 inputs, i.e. longitudinal and lateral accelerations, vehicle speed, and pitch angle signals.

III. Braking Behavior Model

In this section, the focus is on the braking behaviors of truck drivers to evaluate the risk of different types of braking. In different traffic situations, how the brake pedal is pressed and depressed is essential in addition to the frequency and magnitude of each brake. The braking behavior model extracts such features from longitudinal acceleration patterns during brake evens.

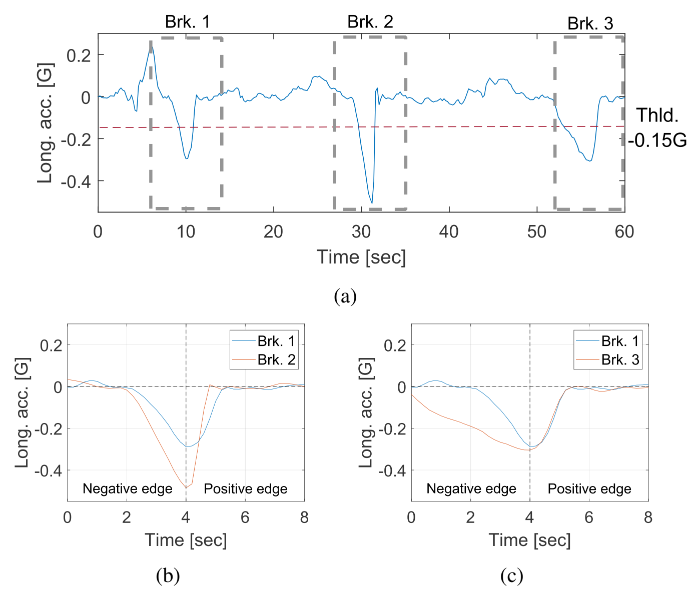


Fig. 3. Example longitudinal acceleration data during different types of brakes (a), brake patterns with different magnitudes (b), and operation times (c).

For each brake event with maximum deceleration greater than a threshold, a T second longitudinal acceleration segment is extracted (Fig. 3a), similarly to [8]. Each segment is centered at its local minimum, and the patterns before and after the local minimum are named negative and positive edges respectively (Fig. 3b). In this model, the magnitude threshold is determined much lower (0.15G), aiming to evaluate most deceleration events only excluding minor speed adjustments and small brakes during busy traffic, unlike the paper [8] that targets only rapid deceleration patterns. Additionally, the duration of segments is determined as 8 seconds, which is designed to capture the complete interval of truck drivers press and depress the brake pedal, which is generally longer than the duration for car drivers.

Single-handedly, the magnitude of the deceleration can be misleading in different traffic situations. For instance, the magnitude of decelerations in brake 1 and 3 are similar however, in brake 3 the driver is considered to be more aware of the traffic and acted in advance to related situations. Still, the brake 2 is an indication of a riskier behavior than brake 1 due to the higher magnitude of deceleration (Fig. 3c-b).

To evaluate the braking in terms of the awareness of the driver, two lines are fitted into the patterns in the negative and positive edges of a segment. Both negative and positive edge lines are designed as a fit between two points, one is fixed at the local minimum (center), and the other is iteratively moved from edge to the center of the segment through data points. The iteration stops when the sum of shortest distances between remaining data points and the line is lower than a certain threshold for both lines (Fig. 4). Brake patterns with steeper negative edge and shallower positive edge lines are considered to represent more aggressive driving behaviors.

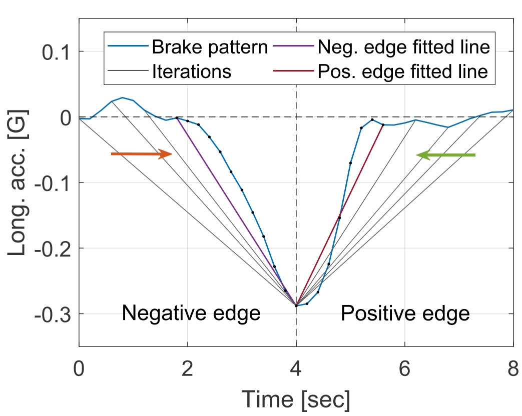


Fig. 4. Negative and positive edge line fitting iterations.

IV. Driver Evaluation Method

A. Evaluation of Acceleration Behavior

To evaluate a truck driver's acceleration behaviors, each T second of his/her driving data is classified into specified driver categories using the acceleration behavior model, in real-time. Additionally, for each road part that is driven during classified driving sequences, the horizontal curve central angle is calculated from the GPS signals. For each T seconds of driving, the driver gets an acceleration score, based on the acceleration behavior model output and the curvature level of the road part.

TABLE III
ACCELERATION BEHAVIOR EVALUATION OF DRIVER CLASSES

	Lateral Acceleration Behavior			
	Calm (+) score in curvy roads	**Moderate** (no effect to overall score)	**Aggressive** (-) score in curvy roads	
Aggressive (-) score in straight roads	Driver 4	Driver 5	Driver 6	**Longitudinal Acceleration Behavior**
Calm (+) score in straight roads	Driver 1	Driver 2	Driver 3	

Different score evaluations are designed for straight and curvy roads, because of the longitudinal and lateral acceleration characteristics of defined classes, as in Table III. For instance, being classified as Driver 4 is penalized ($-\lambda_{acc}$) in straight roads due to the aggressive longitudinal acceleration behavior, however, it is rewarded ($+\lambda_{acc}$) in curvy road sections due to the calm lateral acceleration behavior of this class.

B. Evaluation of Braking Behavior

Braking behavior evaluation of a truck driver is obtained by an event-based approach. For each brake operation, analyzed by the braking behavior model, the overall braking score is modified by ΔS_{Brk}, which is a linear combination of brake form evaluations (negative edge score S_{NE}, positive edge score S_{PE}, minimum G score S_{MinG}), and brake frequency evaluation (S_{freq}) as follows:

$$\Delta S_{Brk} = 0.15 S_{NE} + 0.15 S_{PE} + 0.2 S_{MinG} + 0.5 S_{freq} \quad (4)$$

Brake form evaluation functions are designed to give scores in $\{-\lambda_{brk}, +\lambda_{brk}\}$ range, using the tanh function, defined by the following equations:

$$S_{NE} = -\lambda_{brk} tanh(\alpha_1(|m_{NE}| - \mu_{NE})) \quad (5)$$

$$S_{PE} = +\lambda_{brk} tanh(\alpha_2(|m_{PE}| - \mu_{PE})) \quad (6)$$

$$S_{MinG} = -\lambda_{brk} tanh(\alpha_3(|MinG| - \mu_{MinG})) \quad (7)$$

where m_{NE}, m_{PE} are negative edge line and positive edge line slopes, and MinG is the minimum acceleration of the brake. μ_{NE}, μ_{PE}, are the nominal slope values, μ_{MinG} is the nominal MinG value where the desired score output is zero. Finally, $\alpha_{1,2,3}$ parameters are defined to stretch the tanh function to tune the score outputs, and $tanh(\cdot)$ is defined as

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (8)$$

The negative edge score function is shown, as an example, in Fig. 5a. The braking frequency score is proposed in (9), to penalize repetitive braking actions, which is defined in $\{-\lambda_{brk}, 0\}$ range using the sigmoid function.

$$S_{freq} = \begin{cases} 0 & N_{BE} < 3 \\ -\lambda_{brk}\sigma(\beta(-N_{BE} + \lambda_{brk}/2)) & N_{BE} \geq 3 \end{cases} \quad (9)$$

where N_{BE} is the number of analyzed brake events in a time period and β is the stretching parameter for the sigmoid function, where the sigmoid $\sigma(\cdot)$ is defined as

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{10}$$

Braking frequency evaluation give negative scores for each repetitive break after the second one, as in Fig. 5b.

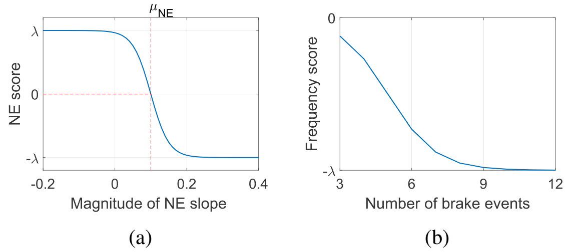


Fig. 5. Negative edge score function (a), brake frequency score function (b).

V. Results

In this section, training and test simulations for the acceleration behavior model, LSTM based driver classification results, examples of acceleration behavior and braking behavior evaluations are presented.

A. Acceleration Behavior Classification

Desired longitudinal and lateral aggression levels for specified drivers can clearly be observed from the overall training and test simulations (Fig. 6). However, all drivers cover intersecting acceleration and speed ranges in varying road conditions. For example, a driving sequence with max. vehicle speed of $50km/h$, longitudinal acceleration of $0.3m/s^2$, and lateral acceleration of $0.2m/s^2$ can be obtained by any of specified drivers. Therefore, it is essential to learn sequential relations between vehicle dynamics signals to recognize different driving behaviors.

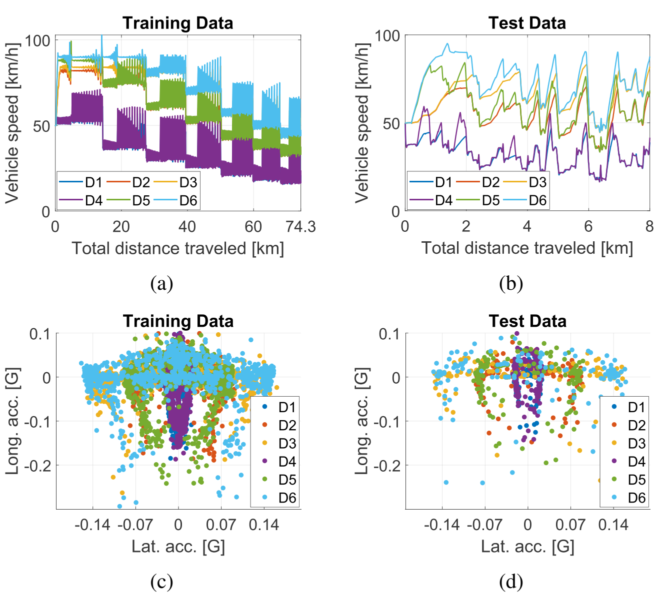


Fig. 6. Driver comparison from acceleration model simulations. Speed profiles (a,b), and acceleration coverage plots (c,d) of drivers in training and test runs.

Using simulated driving data of designed drivers, the LSTM network is trained and evaluated. Input sequences of the network are prepared as illustrated in Fig. 2 to classify acceleration behaviors. The selected parameters for this model and classification results are provided in Table IV.

TABLE IV
Model Parameters and Classification Results

Model Parameters		Classification Results		
Window length	150 (30 sec * 5 Hz)		Training	Test
Window stride	75 (15sec * 5 Hz)	Accuracy	85.75	66.46
# of input signals	4	F1 score	86.43	66.41
LSTM input size	150 x 4	# of trained epochs	148	
Softmax output size	6 x 1			
Learning rate	0.01			
Batch size	300			
# of hidden units	80			

In driving simulations, drivers with the common parameters show similar behaviors in certain road geometries, as expected. This leads to inevitable misclassifications, which can be observed from the confusion matrixes (Fig. 7) as patterns parallel to the correct classification diagonal. However, these misclassifications do not pose a problem for the overall algorithm due to the proposed evaluation methodology in Table III.

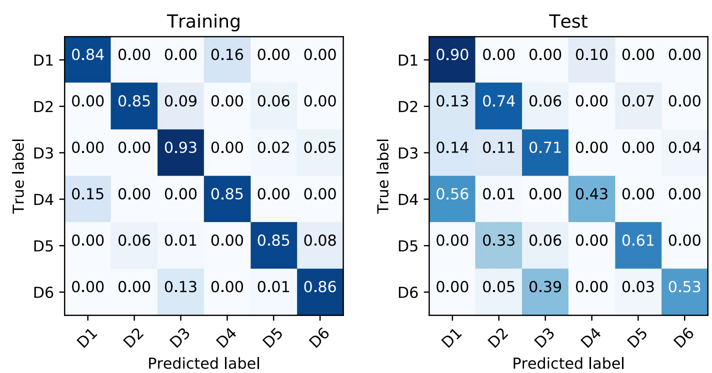


Fig. 7. Normalized confusion matrix of acceleration behavior model classifications for training and test sets.

Drivers with higher aggression levels (longitudinally or laterally) are more often misclassified than less aggressive drivers in the test set (Fig. 7). This is because, in some road conditions, aggressive drivers can show similar behaviors to calm or normal drivers. On the other hand, drivers with lower aggression levels do not show aggressive driving behaviors since they cannot exceed their defined acceleration limits. As the calmest driver within the specified classes, Driver 1 is classified with the highest test accuracy (90%), and Driver 4 is classified with the lowest test accuracy (43%) which is an aggressive driver in terms of longitudinal acceleration.

B. Driver Evaluation

To visualize example evaluations of acceleration and braking behaviors, a 720-sec long driving scenario is generated. In this scenario, the driver controlled the truck as one of the aggressive, normal, and calm drivers respectively for equal time periods. Vehicle and acceleration signals, extracted deceleration patterns, and related acceleration and braking evaluations from this scenario are shown in Fig. 8.

The decreasing aggression level of the driver can be observed from the acceleration behavior evaluations. The acceleration behavior model updates the acceleration score at every 15 seconds after a new class prediction is obtained. The LSTM network classified the driving samples with 72.3% accuracy (34/47 true predictions), and only one misclassification led to an incorrect evaluation when combined with road curvature information.

During this driving scenario, the braking behavior model analyzed 7 braking events, that have a higher deceleration magnitude than the defined threshold (0.15G). The braking score is updated after each brake based on the deceleration pattern and frequency analysis ($\lambda_{brk} = 20$). For instance, while the driver is rewarded for the brakes at t=384 and t=403 due to early anticipation and reasonable deceleration magnitudes, he/she is penalized more than 10 points for the brake event at t=382, because of the undesired pattern, high magnitude, and frequency of the brake (the 3rd significant brake in two minutes).

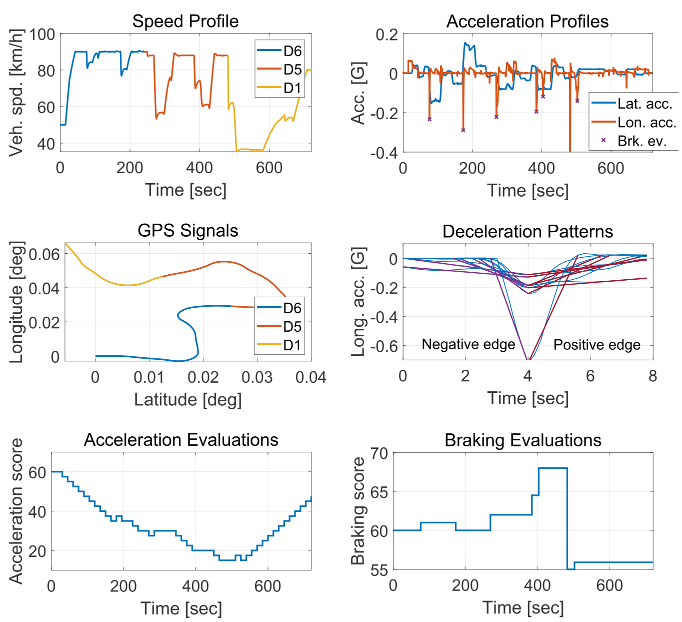


Fig. 8. An example driving scenario for the evaluation of acceleration and braking behaviors.

VI. Conclusion

In this paper, we have presented a system to evaluate the acceleration and braking behaviors of heavy-duty vehicle drivers. Designing such a system for the vehicles with highly varying weight and dynamics is substantial for the vehicle and overall road safety. Classification results show the substantial capability of designed LSTM structure, in the recognition of dynamic relations between driving signals. Proposed acceleration and braking models achieved great results in both driving behavior classification and evaluation. As a future work, developed evaluation system will be implemented to a semitrailer truck. Additionally the evaluation of different driving behaviors will be investigated such as car-following, the use of cruise control, or autonomous driving.

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References

[1] G. Meiring and H. Myburgh, "A Review of Intelligent Driving Style Analysis Systems and Related Artificial Intelligence Algorithms," Sensors, vol. 15, no. 12, pp. 30653–30682, 2015.
[2] T. P. Wenzel and M. Ross, "The effects of vehicle model and driver behavior on risk," Accident Analysis & Prevention, vol. 37, no. 3, pp. 479–494, 2005.
[3] H. J. Walnum and M. Simonsen, "Does driving behavior matter? An analysis of fuel consumption data from heavy-duty trucks," Transportation Research Part D: Transport and Environment, vol. 36, pp. 107–120, 2015.
[4] H.-B. Kang, "Various Approaches for Driver and Driving Behavior Monitoring: A Review," 2013 IEEE International Conference on Computer Vision Workshops, 2013.
[5] M. E. Mumcuoglu, "Driving behavior classification for Heavy-Duty vehicles using LSTM Networks," MSc Thesis, 2019.
[6] K. Saleh, M. Hossny, and S. Nahavandi, "Driving behavior classification based on sensor data fusion using LSTM recurrent neural networks," 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), 2017.
[7] T. Imamura, H. Yamashita, M. R. B. Othman, Z. Zhang, and T. Miyake, "Driving behavior classification river sensing based on vehicle steering wheel operations," 2008 SICE Annual Conference, 2008.
[8] A. Naito, C. Miyajima, T. Nishino, N. Kitaoka, and K. Takeda, "Driver evaluation based on classification of rapid decelerating patterns," 2009 IEEE International Conference on Vehicular Electronics and Safety (ICVES), 2009.
[9] C. Miyajima, H. Ukai, A. Naito, H. Amata, N. Kitaoka, and K. Takeda, "Driver risk evaluation based on acceleration, deceleration, and steering behavior," 2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2011.
[10] M. E. Mumcuoglu, G. Alcan, M. Unel, O. Cicek, M. Mutluergil, M. Yilmaz, and K. Koprubasi, "Driving Behavior Classification Using Long Short Term Memory Networks," 2019 AEIT International Conference of Electrical and Electronic Technologies for Automotive (AEIT AUTOMOTIVE), 2019.
[11] L. Eboli, G. Mazzulla, and G. Pungillo, "Combining speed and acceleration to define car users' safe or unsafe driving behaviour," Transportation Research Part C: Emerging Technologies, vol. 68, pp. 113–125, 2016.
[12] G. Reymond, A. Kemeny, J. Droulez, and A. Berthoz, "Role of Lateral Acceleration in Curve Driving: Driver Model and Experiments on a Real Vehicle and a Driving Simulator," Human Factors: The Journal of the Human Factors and Ergonomics Society, vol. 43, no. 3, pp. 483–495, 2001.
[13] R. Akcelik and D. C. Biggs, "Acceleration Profile Models for Vehicles in Road Traffic," Transportation Science, vol. 21, no. 1, pp. 36–54, 1987.
[14] L. Eboli, G. Mazzulla, and G. Pungillo, "Combining speed and acceleration to define car users' safe or unsafe driving behaviour," Transportation Research Part C: Emerging Technologies, vol. 68, pp. 113–125, 2016.
[15] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.