Driving Behavior Classification Using Long Short Term Memory Networks

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***Abstract*—Researchers in the automotive industry aim to enhance the performance, safety and energy management of intelligent vehicles with driver assistance systems. The performance of such systems can be improved with a better understanding of driving behaviors. In this paper, a driving behavior recognition algorithm is developed with a Long Short Term Memory (LSTM) Network using driver models of IPG's TruckMaker. Six driver models are designed based on longitudinal and lateral acceleration limits. The proposed algorithm is trained with driving signals of those drivers controlling a realistic truck model with five different trailer loads on an artificial training road. This training road is designed to cover possible road curves that can be seen in freeways and rural highways. Finally, the algorithm is tested with driving signals that are collected with the same method on a realistic road. Results show that the LSTM structure has a substantial capability to recognize dynamic relations between driving signals even in small time periods.**

Keywords—Driver behaviors, classification, intelligent vehicles, LSTM networks, acceleration behavior

I. INTRODUCTION

As the world goes into the direction of intelligent and autonomous vehicles, human is still an essential part of the current vehicle technology. Human drivers and their behaviors have been studied through years for different vehicle applications. Improving fuel/power efficiency of a vehicle is the primary motivation in the majority of those studies. Incorrect driving behaviors lead to dramatic fuel/power consumption changes especially for high loaded vehicles such as heavy-duty trucks [1]. Guo et al. [2] claimed that fuel consumption of a 25 tons GCW commercial truck dropped 25 % by detecting and fixing those driving behaviors with some driving tips. Driving characteristics and a driver's physical state plays a vital role also in road safety. Researchers and industry have developed a lot of different methods that investigate driving behaviors and visual features of drivers to detect risky driver states (e.g., fatigue, drunk, drowsy) [3]. Advanced driver assistance systems (ADAS) is a popular field of research that aims to improve the safety and efficiency of vehicles with assisting drivers during specific events. Designing such systems based on driver characteristics, rather than generic driver models, may increase the performance of the system for different drivers [4-5].

Nevertheless, recognition of different driving behaviors in different conditions is necessary to accomplish performance, safety, and fuel/power economy improvements. Various driving signals and classification methods are used for driving style recognition algorithms [6]. Longitudinal – lateral acceleration, vehicle speed, fuel consumption, throttle position, brake pressure, distance to forward vehicle are some of the highly preferred signals as an input for such algorithms [7-11]. Those signals characterize driving behaviors well, in different situations. They can be acquired with high sensitivity from the vehicle's onboard IMU [7], GPS [8] and Radar/LiDAR [9] sensors. With existing technology, collecting some of those signals using a smartphone sensor is also a popular and reliable alternative to be used in such algorithms [10,11].

Fundamentally, driving characteristics are extracted with two different methodologies i.e., direct methods and indirect (model-based) methods [12]. For recognition purposes, direct methods directly analyze driving signals, generally using pattern recognition or data analysis techniques. On the other hand, indirect (model-based) methods need to define a driver model to identify driving behaviors.

Zhang et al. [13] proposed a direct driving skill characterization method from the perspective of pattern recognition. Their algorithm includes multilayer perceptron-artificial neural networks (MLP-ANN), decision tree, and support vector machines. Wang and Xi [12] also proposed a combine k-means clustering-support vector machines (kMC-SVM) algorithm as a direct pattern recognition method for Driving Styles. Saleh et al. [14] used many-to-one recurrent neural networks (RNN) to classify drivers into normal, aggressive and drowsy. Hidden Markow Model (HMM) networks as a stochastic process are widely used for modeling driving behaviors [15]. Those models can determine relations between observations and behaviors dynamically. [16] proposed a probabilistic autoregressive exogenous (ARX) model to classify drivers current driving style.

In this paper, we propose a dynamic algorithm with a Long Short Term Memory (LSTM) classifier to identify driver models that are designed based on longitudinal and lateral acceleration limits. Six driver models are generated in the simulation environment without labeling specifically (i.e., aggressive, moderate, smooth) to mimic real driving behaviors in different road conditions. An LSTM structure is trained with driving signals of those drivers in a small time-window. The signals are generated using a realistic truck model with five different trailer loads on an artificial training road. Longitudinal and lateral acceleration, engine and vehicle speed, throttle position and pitch angle signals of the vehicle are selected as classification model inputs to train the model with driving outputs as a reaction to the road geometry. LSTM structure have successfully recognized driving behaviors in small time samples.

The remaining of this paper is organized as follows, in the Section II, the design of experiment is explained with the discussion of the road and driver models. The methodology of the data generation, classification algorithm and the structure of the used LSTM network are presented in the Section III.

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Results are discussed in the Section IV. Finally, conclusions are provided in the Section V.

II. Experiment Design

In this section, the methodology of training and test road designs and driver models are discussed. The road and the driver models are used in driving simulations to acquire the data for classification, which is explained in a further section.

A. Training & Test Road Design

In this paper, an artificial training road is designed to extract the driving behaviors of a driver model as responses to different road profiles. It is aimed to train the proposed algorithm with driving signals covering most of the possible road geometries of a freeway or a rural highway.

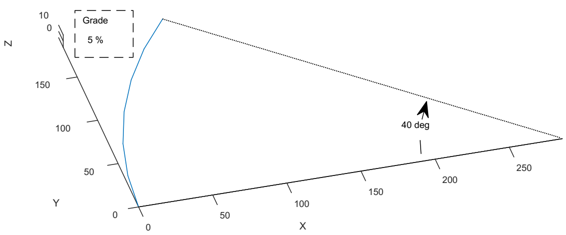
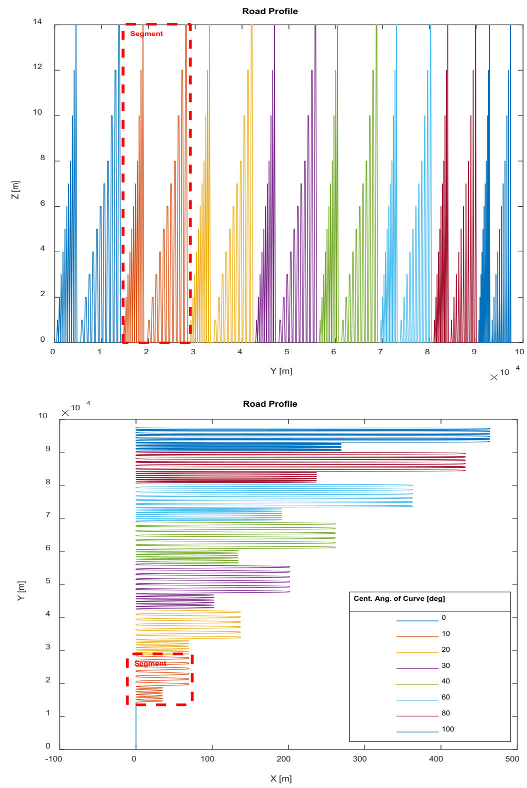


Fig. 1. X-Y-Z profile of an example road block.

To generate simulation routes systematically, the road block concept is generated. A road block is designed to be 200 m length of an arc that is defined by 6 points in 3D space. It represents a small portion of a road with constant grade and horizontal curve profile (without superelevation). A road block has two parameters which are grade of the road in percentage and central angle of the horizontal curve in degrees. Several road blocks are aligned to form a complete training/test road for simulations.

(a)



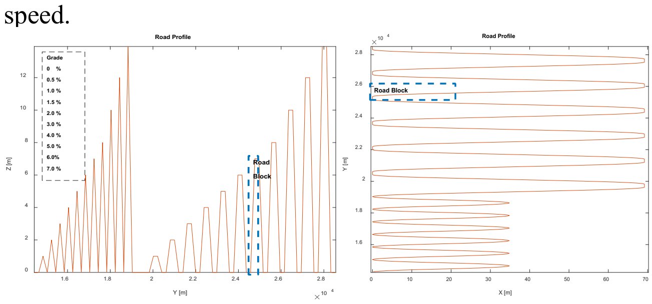
(b)

Fig. 2. (a) Z-Y profile and (b) Y-X profile of the training road.

The grade parameter represents uphill when it is positive and downhill when it is negative. The central angle parameter represents a right-turn when it is positive, a left-turn when it is negative, and a straight road when it is zero. An example of a road block is presented in Fig. 1.

In order to increase the modeling accuracy for different road types, the training road is targeted to cover different combinations of grade – central angle parameters in desired ranges. Those ranges are determined based on the radius of the curvature and the length of the grade [17]. To cover determined ranges, 8 road segments are designed. Segments follow the same grade and horizontal curve pattern with a different central angle value and depicted in Fig. 2 with different colors.

Altitude and curvature profile of a road segment consists of two parts. In the first part, road blocks with positive and negative grades are positioned next to each other from lower slopes to higher slopes. This part composes different vertical crest and sag curves. In the second part, there is one road block with 0 % grade in after each uphill and downhill block (Fig. 3, Z-Y profile). The same pattern is used for horizontal curves with one central angle value in a segment (Fig. 3, Y-X profile). The plain road blocks between curves will let driver models accelerate starting from different speeds to reach their target speed.



(a) (b)

Fig. 3. (a) Z-Y and (b) Y-X profiles of an example training road segment.

The designed training road is 114.7 km, that involves 8 road segments with 72 road blocks in each. In this road, lower grade - centeral curve intersections are covered more densely, since the existence of simultaneous sharp curvatures and high grades in a highway is uncommon. Finally, an 8 km, smoother road is designed using road blocks with arbitrary parameters to test the developed algorithm. Coverages of the training and test roads are shown in Fig. 4.

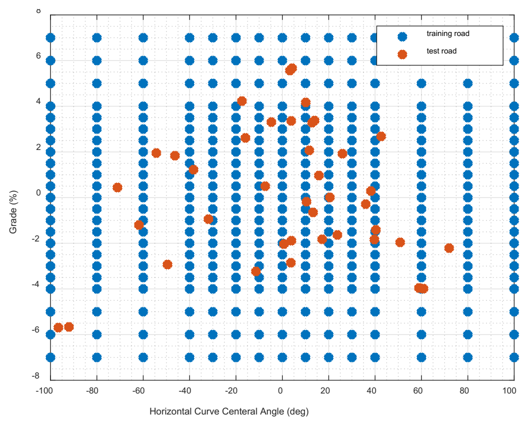


Fig. 4. Grade - centeral angle of horizontal curve covarage map for training and test roads.

B. Driver Design

In literature, it is known that acceleration signals can describe distinctive features of different driving behaviors. T. Krotak and M. Simlova [18] showed that, different driving behaviors of a beginner and an expert driver reflect on longitudinal - lateral acceleration signals significantly. In the light of this information, we develop our algorithm using the driver model of IPG's commercially available software TruckMaker [19] that is parameterizable based on acceleration behaviors.

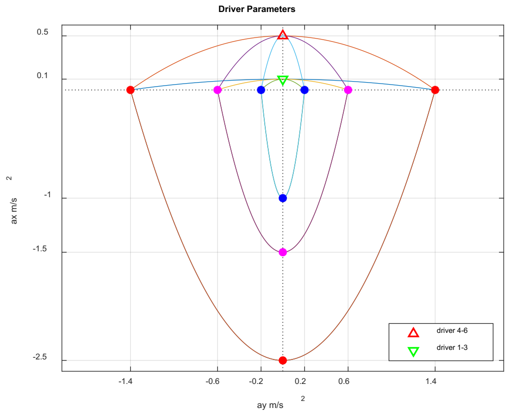


Fig. 5. Driver acceleration limit parameters.

The driver model of TruckMaker continuously generates target speeds with previewing the road curves to reach a cruising speed without exceeding certain acceleration limits. The model operates the vehicle at those target speeds using a PI controller that generates throttle and brake outputs, as a real driver. To mimic real driving behaviors, we set five of the driver model parameters i.e., maximum longitudinal acceleration and deceleration (braking), maximum lateral accelerations for left and right turns and the cruising speed.

TABLE I. DRIVER PARAMETERS

Driver Num.	***Speed limit***	***Longitudinal acc. limit parameters***		***Lateral acc. limit parameters***	
	Tx [hph]	***ax_t [m/s²]***	***ax_b [m/s²]***	***ay_l [m/s²]***	***ay_r [m/s²]***
1	90	0.1	2.5	1.4	1.4
2	90	0.1	1.5	0.6	0.6
3	90	0.1	1.0	0.2	0.2
4	90	0.5	2.5	1.4	1.4
5	90	0.5	1.5	0.6	0.6
6	90	0.5	1.0	0.2	0.2

Six driver classes are designed for the simulations using the parameters given in Table I. First three drivers (Driver 1-3) have lower longitudinal acceleration limits than the last three drivers (Driver 4-6). Lateral acceleration and (braking) deceleration limits are decreasing gradually (from driver 1 to 3, or driver 4 to 6) in each set. Drivers with the same lateral and different longitudinal acceleration limits are named as differing classes due to their similar behaviors in some conditions. Acceleration limits of drivers are visualized in Fig. 5.

III. DRIVER CLASSIFICATION

A. Data generation

Driving data for the proposed classification algorithm is generated using IPG's TruckMaker vehicle dynamics simulation software. For our task, an accurate physical model of a commercial Ford Truck is created using the real parameters and properties of the vehicle, i.e., engine, powertrain, transmission parameters, and mass, inertia, dimensional properties. Each driver is simulated on both training and test roads using the vehicle model with 5 different trailer loads, i.e., 0, 5, 10, 15, 20 tones. In total, 60 different driving data of six driver classes is recorded at 5 Hz.

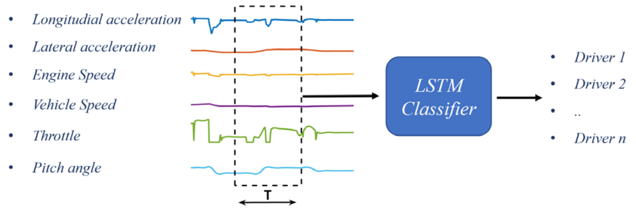


Fig. 6. Classification model inputs.

Longitudinal and lateral accelerations, engine and vehicle speeds, and pitch angle of the vehicle have been selected as inputs to the proposed algorithm. 30 second time-window (*T*) is shifted through all the driving data with the period of 15 seconds. The signals within the window are labeled with its driver number and used as a sample for classification model (Fig. 6).

B. LSTM Networks

In order to classify the driving behavior, the temporal relations of the selected inputs are targeted to be explored. For this purpose, a type of recurrent neural network called Long Short Term Memory (LSTM) [20] network is selected.

A typical LSTM neural network includes an input layer, a recurrent hidden layer and an output layer. Different from classical neural networks, LSTM networks have memory capabilities with three gates called: forget gate, update gate and output gate (Fig. 7).

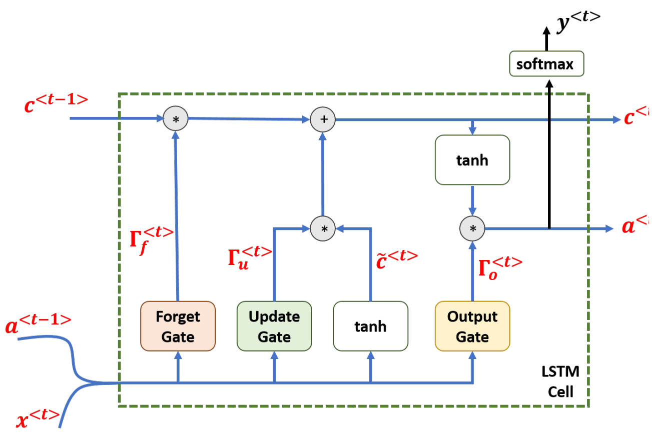


Fig. 7. Long short term memory network structure.

The gates in an LSTM structure are independent neural networks with the same dimension and sigmoid activation functions. Input to these gates is the concatenation of measurements ($x^{<t>}$) and the output state of previous LSTM cell ($a^{<t-1>}$). In this study, measurements include the signals shown in Fig. 6 for a time period of T.

Forget gate adjust the information to discard from the cell, update gate and tanh gate decide the values from the input to update the memory state ($c^{<t>}$), and output gate determines what to output based on input and memory of the cell. A typical LSTM neural network can be implemented by the following equations

$$\Gamma_f = \sigma(W_f[\,a^{<t-1>}, x^{<t>}] + b_f) \tag{1}$$

$$\Gamma_u = \sigma(W_u[\,a^{<t-1>}, x^{<t>}] + b_u) \tag{2}$$

$$\tilde{c}^{<t>} = \tanh(W_c[a^{<t-1>}, x^{<t>}] + b_c) \tag{3}$$

$$\Gamma_o = \sigma(W_o[\,a^{<t-1>}, x^{<t>}] + b_o) \tag{4}$$

$$c^{<t>} = \Gamma_u * \tilde{c}^{<t>} + \Gamma_f * c^{<t-1>} \tag{5}$$

$$a^{<t>} = \Gamma_o * c^{<t>} \tag{6}$$

where W_f, W_u, W_c, W_o, W_r are the weight matrices and b_f, b_u, b_c, b_o, b_r are the bias vectors of corresponding operations.

At the end of the recurrent calculations of (1)-(6) for a time period (T), the last output state ($a^{<last>}$) is fed to the output layer and employed in softmax function to find the probabilities for each class as follows:

$$z = W\,a^{<last>} + b \tag{7}$$

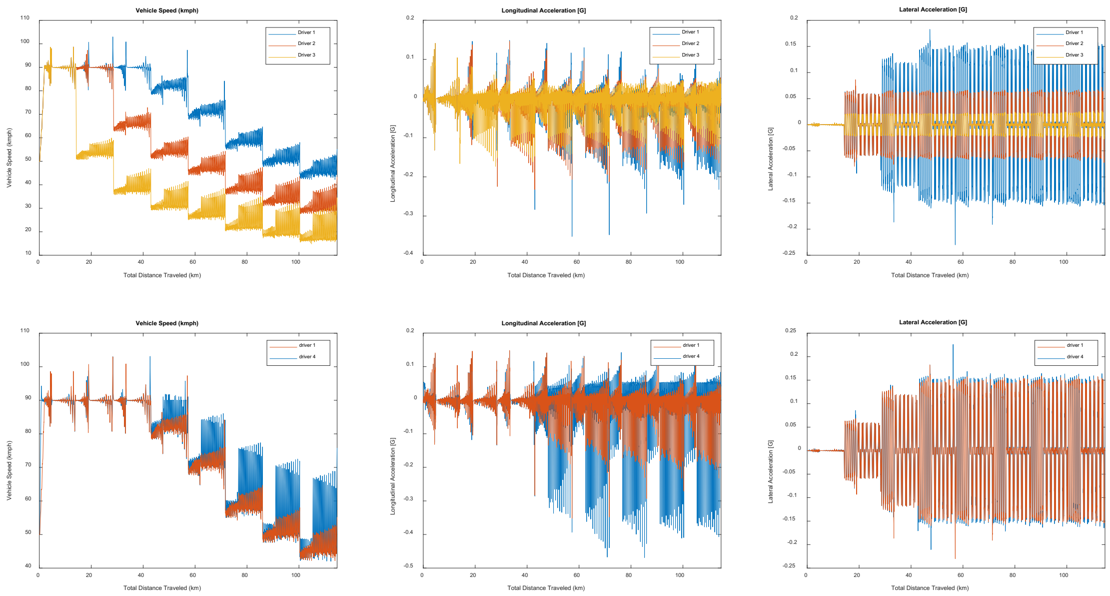
$$softmax(X_i) = \frac{exp(X_i)}{\sum_{j=1}^{k} exp(X_j)} \tag{8}$$

$$i = 1,2,\ldots,k$$

where W and b are the weight and the bias vectors in the output layer, and k is the number of classes.

IV. Results

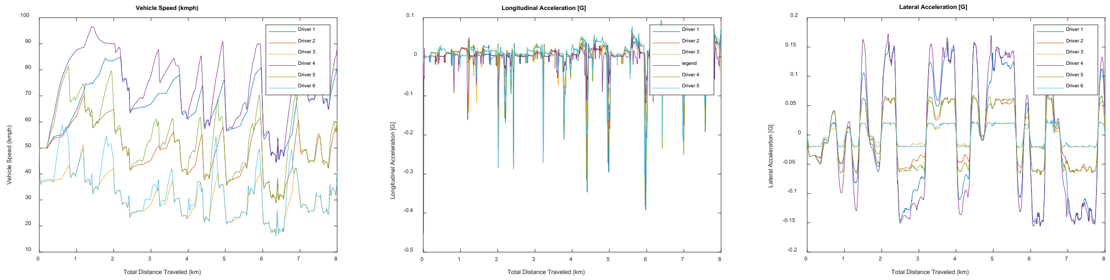
In this section, driving behaviors of designed driver models are compared using speed and acceleration signals of simulation outputs. Results of the proposed LSTM network based classification algorithm and related discussions are also provided.



(a)

(b)

Fig. 8. Driver comparison based on vehicle speed, longitudinal and lateral acceleration signals from the training road (10 tons of trailer load). (a) Drivers in the same set. (b) Drivers in a differing class.



(a) (b) (c)

Fig. 9. (a) Vehicle speed, (b) Longitudinal, (c) lateral acceleration signals of all six drivers from the test road (10 tons of trailer load).

A. Driver Comparison

The effects of selected driver parameters can be easily observed from the signals presented for different segments of the training road (Fig. 8). For instance, the lateral acceleration plot in Fig. 8 (a) shows that the Driver 1 remains in the $| a_y | < 1.4$ m/s^2 band while Driver 2 in $| a_y | < 0.6$ m/s^2 and Driver 3 in $| a_y | < 0.1$ m/s^2 during the whole trip. To obtain such conditions, those three models operate with various speed profiles in different curves. Longitudinal acceleration behaviors slightly vary between these models as expected. A similar comparison could be made between the last three drivers.

It is also significant to compare the drivers with the same lateral acceleration limits. In that sense, comparison of driving speed, longitudinal and lateral acceleration signals for Driver 1- 4 is given in Fig. 8 (b). Driver 4 has operated with a higher longitudinal acceleration profile than Driver 1, while the lateral acceleration profile is almost the same. However, all driving signals of such driver couples overlap in some cases that can be observed easier from the test road. We have named those driver couples as "differing class" for further discussions, i.e., Driver 1-4, 2-5, 3-6.

B. Classification Results

The proposed LSTM network structure is trained and tested with the driving signals of drivers in a small time-window. Those driving signals are collected using a realistic truck model with five different trailer loads. The dynamics of the vehicle change significantly based on the mass of the vehicle.

Experiments have shown that size of the window (T) considerably affect the classification results. When the T is too small, sample data become insufficient to distinguish drivers. On the other hand, a large T lead to unrealistic signal forms due to the repetitive nature of the training road. As a result, a 30 second window is selected that provide decent amount of information about driving behaviors in each sample. Additionally, shifting the window with the period of 15 seconds have enhanced the training performance.

(a) (b)

Fig. 10. Normalized confusion matrix of the training (a) and the test set (b).

Classification accuracies of the training and the test sets are respectively 82.24 % and 74.70 %. Confusion matrix of training and test roads (Fig. 10) show that, majority of the misclassifications made between differing classes. When differing classes are assumed as correct outputs, the accuracy of training and test sets are respectively, 93.1 % and 92.8 % (Fig. 11). Although, a differing classification cannot be labeled directly as a true output, there is a high chance that differing classes behave the same in the majority of misclassified samples.

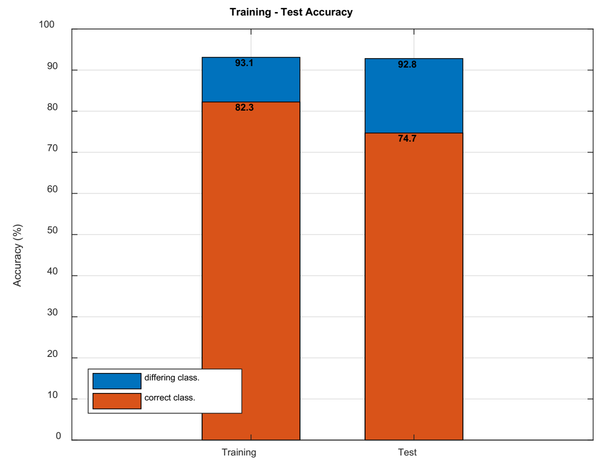


Fig. 11. Training and test accuracy graph for correct and differing classes.

Nevertheless, the classification results have proven that the proposed LSTM structure is effective at extracting dynamic driving behaviors of drivers in a limited time-window.

V. Conclusion

We have now proposed a new method using a Long Short Term Memory (LSTM) structure, with the aim of the recognition of different driving behaviors in small time periods. Six driver models are designed based on longitudinal and lateral acceleration using the driver model of IPG's TruckMaker. Driving signals of those driver models are generated using a realistic truck model with varying carry loads. An artificial training road is designed to simulate possible road geometries and to learn driving behaviors of designed driver models. Additionally, with such design we can analyze driving signals (e.g., longitudinal - lateral accelerations, fuel consumption) as driver response to different road geometries.

Results show that the LSTM structure has the capability of recognizing dynamic relations of driving signals even in small time periods. With the improved ability of the current simulation technology, the proposed algorithm can be adapted to different vehicles with high sensitivity. The proposed algorithm can recognize driving behaviors of real drivers dynamically in discreate time that can be used to enhance the performance of an ADAS system.

As future work, prediction errors and differing classifications will be investigated to improve road and driver designs. The designed algorithm will be tested on real drivers. Current driver models will be extended based on different driving behaviors, e.g. traffic or car-following behaviors.

Acknowledgment

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