A personalized Adaptive Cruise Control driving style characterization based on a learning approach

Dario Nava*, Giulio Panzani*, Pierluigi Zampieri and Sergio M. Savaresi*

Abstract— **Advanced Assistance Driver Systems (ADAS) adaptation with respect to driver driving style is a research field of major interest, given the additional benefits that could be obtained in terms of comfort and safety perceived by the user. In this work, a personalized Adaptive Cruise Control (ACC) oriented driving style features extraction method is proposed, meant to be used to choose an ACC tuning which better fits the driver on road behaviour. The method exploits an Artificial Neural Network driver model, capable of capturing the driver behaviour in a car following scenario, trained and validated over real data. From a closed-loop model analysis in a simulation environment driving style features are then extracted, looking at the system response to variations of the preceding vehicle speed. Finally, the effectiveness of the extracted features for a non-trivial characterization of the driver behaviour is assessed, comparing the results obtained considering three different drivers.**

I. Introduction

In the late years, it has undoubtedly been a growing trend to equip new vehicles on the market with Advanced Driver Assistance Systems (ADAS), given the benefits they can bring in terms of comfort and safety of the driver. In the ADAS context, Adaptive Cruise Control (ACC) [1], [2] is the natural evolution of the Cruise Control system. While the latter is a mere vehicle speed controller, the ACC maintains the user-defined speed set point when the road ahead is clear, switching to distance control whenever obstacles are detected, thanks to the information usually retrieved from a radar sensor. Whereas the state-of-the-art in ACC technology is already in an advanced stage, open issues are still related to user acceptance. In fact, since the ACC completely substitutes the human driver in controlling the longitudinal vehicle dynamics during car following, it is essential for its behaviour to be perceived safe and comfortable by users [1], [2]. In such sense, ACC adaptation *w.r.t.* to personal driving style is a research field of great interest [3], that could potentially enhance the advantages brought by the deployment of such technology. However, up to now the great majority of ACC systems available on the market only give the user the possibility to manually choose among a certain number of predefined ACC settings the one that satisfies him/her the most, without the implementation of any adaptation or personalised strategy.

A first approach towards the goal of an ACC adaptation *w.r.t.* driver behaviour exploits driving style classification and recognition methods based on learning techniques (see the recent survey [4]). In this setup, in [5] an adaptation method specifically designed for ACC controllers based on a binary driving style classification is proposed. Exploiting a SVM classifier that takes as input driving style characteristic features, drivers are divided in two clusters, calm and sportive behaviour respectively: this information might be used to automatically select the best ACC setting for the driver within a set of labelled tunings.

A different approach to ACC adaptation problem consists in the exploitation of driver models (see [2], [6]) capable of accurately reproducing his behaviour during car following. The ACC system is then designed so to mimic the identified behaviour: typically the driver model is used to produce targets for different variables in a car following scenario. For example, in [7] a driver physical model for steady car-following is presented that, identified on real driving data by means of Recursive Least Squares, is able to generate throttle/braking pressure according to the driver driving style. The model output is given as reference to a PID controller, that generates the control action. Similarly, in [8]–[10], a model, combination of Hidden Markov Model and Gaussian Mixture Regression, is trained on driving data. Such model produces as output the desired vehicle acceleration sequence over a prediction horizon, emulating the driver behaviour. Its output is given as input to an MPC controller, which generates a final safe acceleration sequence to be applied as control action in autonomous mode. A features based learning-from-demonstration method is applied in [11], where a driver model is trained, capable of producing driving trajectories during car following similar to the ones shown by the driver. In [12] and [13] Neural Network black-box models are exploited. In [12] the suitability of deploying both Feedforward and Elman Neural Networks to identify human driver behaviour during car following is assessed. In [13] instead, a Forward Neural Network is trained to capture the driver behaviour, producing as output a desired distance to be maintained from the preceding vehicle. Such set point is then given as input to a PID controller.

The work presented in this paper lies in between the two discussed approaches. Similarly to the first one, we consider the ACC as characterized by a certain set of pre-defined and unchangeable configurations with the final objective of choosing the one that better matches the driver's behaviour. However, avoiding a too generic driving style labelling and specifically focusing on the driver's behaviour in a car following scenario, we take advantage of a detailed Neural Network model of his/her behaviour and we analyse it in terms of closed-loop dynamic response. Some features that precisely characterize different aspects of the driver closed-loop behaviour are discussed. They could be exploited in future works for ACC adaptation purposes, where the selected ACC tuning is the one that better matches the discussed closed-loop parameters. Indeed, the method could also be applied as to characterize the "equivalent" driving style of different tunings of the ACC.

This idea is partially inspired by the work presented in [14], where a second order linear model is used to describe the driver's behaviour. However, as shown in the following of the paper and testified by the significant amount of works related to driver behaviour modelling, this turns to be a too simplistic assumption.

*Dipartimento di Elettronica, Informazione e Bioingegneria, Politecnico di Milano, Italy.
Corresponding author: giulio.panzani@polimi.it

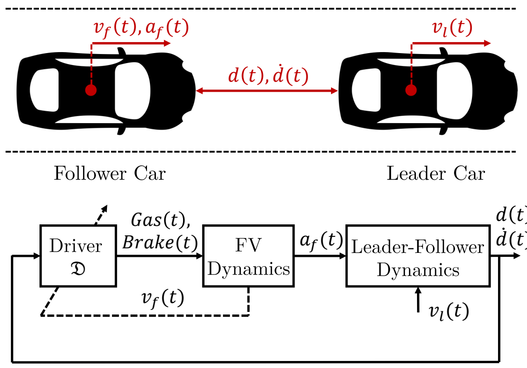


Fig. 1: Car following scenario schemes: general scheme (top) and car following dynamics blocks scheme (bottom).

The remainder of the paper is organized as follows. In Section II the approach used for the characterization of the drivers' behaviour, within a personalised ACC tuning perspective, is presented. In Section III, the Neural Network black-box driver model is presented and trained on real driving data for three different drivers. In Section IV, the ACC adaptation oriented features extraction procedure will be described. Finally, in Section V conclusions and future steps for the presented work are drawn.

II. Problem Definition and Description

A. The Car Following Scenario

Given the ACC application, the driver's behaviour is analysed in a car following scenario which represents the closest driving condition to the autonomous cruise control one. Such scenario [6] consists of two vehicles, a Leader Vehicle (LV) and a Follower Vehicle (FV) both characterized by their speed ($v_l(t)$ and $v_f(t)$ respectively), proceeding at a certain distance $d(t)$, as shown in Figure 1. In the same figure, a block diagram of the car following dynamics is depicted: the system is a closed-loop one where the driver of the FV acts as a controller on the gas/brake pedal based on the perceived distance $d(t)$, speed $v_f(t)$ and relative speed $\dot{d}(t)$. Its objective is to maintain a desired distance from the LV. The decision on which and how to keep such distance is based on different factors that constitute the individual driving style. The pedals pressure exerted by the driver translates, through the FV dynamics, into the instantaneous acceleration $a_f(t)$ of the FV, which regulates the distance $d(t)$ and relative speed $\dot{d}(t)$ between the LV and FV ("Leader-Follower Dynamics" block). In this setup, the LV speed $v_l(t)$ can be seen as a disturbance acting on the system.

It is worth to notice that the described dynamics are highly non-linear both in the FV dynamics (*e.g.* actuators saturation, non-linear engine map, etc.) and, most important, in the driver one which exhibits different behaviours, *e.g.* in response to vehicle speed, distance from the LV, braking or acceleration situations, and so on. In the car following setup, two well-known fundamental quantities must be introduced: the Time Headway (THW) and Time To Collision (TTC) [5], [7]. The THW is the time taken by the FV to reach the actual position of the LV, and gives information about the preferred distance maintained by the FV driver as a function of its speed:

$$THW(t) = d(t)/v_f(t) \tag{1}$$

The TTC is defined as the time interval the FV takes to reach the LV, assuming the two maintaining the actual relative speed, and carries information about the level of crash risk accepted by the FV driver during car following:

$$TTC(t) = \frac{d(t)}{v_f(t) - v_l(t)} = \frac{d(t)}{\dot{d}(t)} \tag{2}$$

In order to avoid numerical issues during a perfect steady-state car following, usually the inverse $TTC^{-1}(t)$ is considered in place of $TTC(t)$.

B. Experimental Setup and Data Collection

The feature extraction approach, described in the following, has been tested on actual experimental data, collected during highway car following driving sessions with a leader and a follower vehicle. In particular, the latter was instrumented with the following devices, likely to be already installed on an ACC equipped vehicle:

- a long range automotive radar, to measure distance $d(t)$ and relative speed $\dot{d}(t)$ between the FV and LV;
- a 6 d.o.f. IMU which, in particular, measures the longitudinal acceleration $a_f(t)$ of the FV;
- wheel encoders to measure the FV speed $v_f(t)$;
- a dSpace MicroAutoBoxII prototyping platform to acquire all the sensors signals at a sampling frequency of 100 $[Hz]$.

In order to collect effective data on drivers' behaviour, the LV was driven at an average speed of 90 $[km/h]$ alternating braking, accelerations and constant speed manoeuvres. Three different drivers alternately drove the FV, chasing the LV according to their own particular driving style. Since the behaviour of the leader has a strong influence on the test protocol, controlling also the leader car during the experiments ensures repeatability: to this end, the same person drove the the LV for the full experimental campaign duration. Altogether, approximately 20 minutes of car following data were recorded for each one of the drivers. For each driver, a training and a validation dataset have been created, the first containing the 75% of acquired samples (training) and the latter the 25% of samples (validation). Examples of the acquired data relative to each driver are depicted in Figure 2 (where the leader speed is obtained as $v_l(t) = v_f(t) + \dot{d}(t)$). Inspecting the signals, it is possible to draw some qualitative conclusions about the driving style of the three drivers. Looking at the FV and LV speeds, it can be seen how for Driver 1 and 3 the leader and the follower speed are close one another almost over the entire test, while in the Driver 2 case the two signals have slightly different trends and a consistent phase delay. Drivers 1 and 3 show a much more reactive behaviour, suggesting a more aggressive driving style *w.r.t.* Driver 2. The inspection of the vehicles distance $d(t)$ corroborates this hypothesis. Indeed Driver 1 and 3 keep, on average, smaller distances from the LV during the tests compared to Driver 2: this leads to smaller values of $THW(t)$ for the first two - once again a symptom of the more aggressive behaviour of Driver 1 and 3. For the sake of completeness, the average distance Time Headway values for the three drivers, namely $\overline{THW}$, held during experimental tests are reported in the caption of Figure 2.

Finally, the inspection of the longitudinal acceleration helps to appreciate the non-linear behaviour of the drivers in general. In fact, the braking manoeuvres compared to the acceleration ones are characterized by higher $|a_f(t)|$ values, due to the greater power available. This unbalance between braking and accelerating dynamics will be better highlighted in Section IV-B.

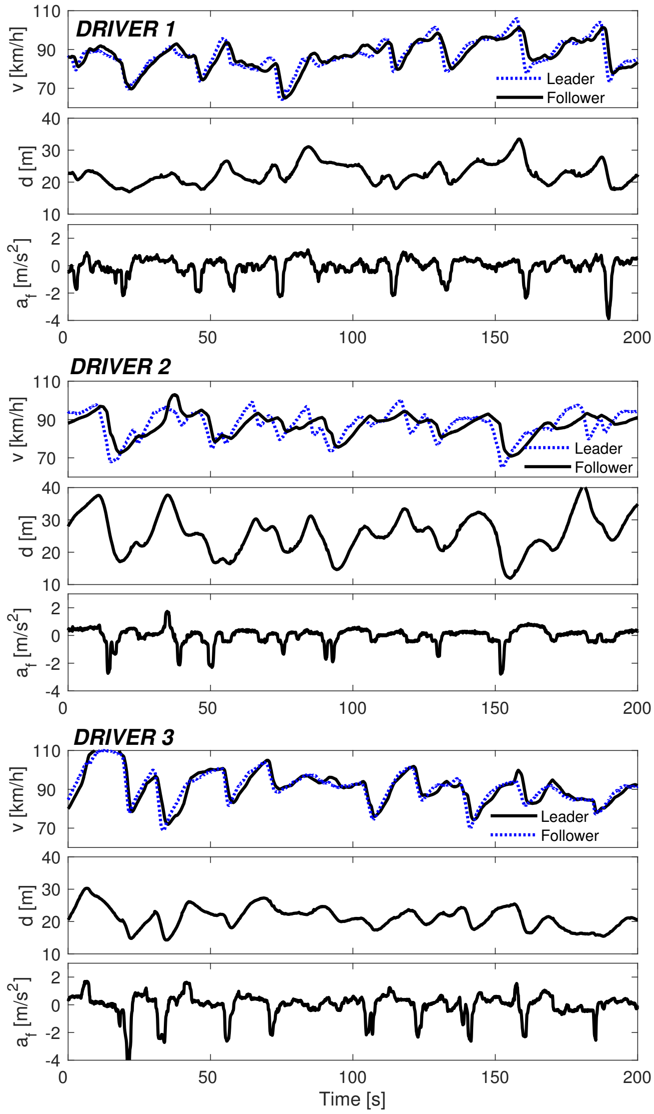


Fig. 2: Examples of experimental data recorded during car following for the three drivers. The average time headways $\overline{THW}$ are $0.92[s]$ for Driver 1, $1.06[s]$ for Driver 2, $0.85[s]$ for Driver 3.

C. Discussion on the proposed approach

One possible approach for ACC personalization, described in the recent work [5], is to infer the drivers' style from the available quantities that describe the overall car following behaviour, like the Time Headway and the Time To Collision. However, such variables are influenced by definition by both the Leader and the Follower driving styles and their sole analysis might thus be misleading: indeed in the mentioned work all results are obtained in a LV constant speed scenario. In view of a possible application in a realistic situation where LV speed variations are accounted for, a two step approach is hence proposed.

Firstly, in order to isolate the FV driver behaviour, we opted for a black-box data driven modelling of his/her driving style, as a dynamic non-linear system that produces vehicle accelerations in response to variations in the LV-FV distance. It is interesting to highlight the role of the LV in such approach: indeed, the higher the variations in the LV behaviour, the more the FV driver inputs are excited, possibly leading to a more accurate description.

Given the complexity and the huge number of parameters needed, a direct comparison among the different driver models is inapplicable. Thus, as second step, each identified model is analysed by inspecting its simulated closed-loop dynamics, aiming at the extraction of some simplified features capable of catching the different drivers' behaviours. The *a priori* knowledge about the style of each driver directs and assesses the effectiveness of the proposed approach.

III. Driver model identification

Following the suggestions of [8]–[10], [14] in this section a model of the driver behaviour is introduced, capable of reproducing his/her dynamics in the car following context. The FV driver is modelled as a dynamic system which produces as output the vehicle acceleration $a_f(t)$ in response to the available measures. In the proposed approach, to account also for differences in the vehicle longitudinal dynamic response, both the driver and FV dynamics will be included in the modelling (see Figure 1).

A. Driver model structure

Due to the complexity and non-linearity of the dynamics involved, the driver modelling problem is herein addressed in a black-box identification framework, exploiting Artificial Neural Networks. A Time Delay Neural Network (TDNN) [15], with time delays on the input stage only, is used. Such network architecture is capable of modelling a dynamic system thanks to its external delays structure but still keeping a reasonable complexity and parameter number, easing its tuning efforts.

The network accepts as input a number m of time series, namely $\mathbf{u}(t) = [u_1(t),...,u_m(t)]^T$. At every time instant t, the last $h+1$ samples $u_i(t-h),...,u_i(t)$ of every *i-th* time series, $i=1,...,m$, are processed by the N hidden layers of the network to produce the final output $y(t)$. Each $j-th$ hidden layer, $j = 1,...,N$, is characterized by a number n_j of artificial neurons. The number of network parameters is a function of the number of inputs m, the value h of the input time delay, the number of hidden layers N and the numbers n_j of neurons for each one of the hidden layers.

In our specific setup, a TDNN structure with a single hidden layer ($N = 1$, with n neurons in the layer) has proved to be sufficient to correctly match the dynamics of interest, as will be shown in the following. The output $y(t)$ of the network is the instantaneous FV acceleration $a_f(t)$, as already explained, whereas for the input variables the THW and the inverse of TTC has been chosen: $\mathbf{u}(t) = [THW(t) \quad TTC^{-1}(t)]^T$. The proposed choice reflects the widely accepted correlation of the two quantities with the scenario under analysis. Moreover, it allows to reduce the number of inputs - thus the model parameters - as the two variables, see (1) and (2), are a non-linear combination of three measures: the vehicle speed $v_f(t)$, the distance $d(t)$ and its derivative $\dot{d}(t)$.

B. Model structure selection and training

The experimental data collected for each driver are employed to train his/her black-box model. In order to fully determine the model structure, the values of n and h that lead to the best modelling performances must be found. For fixed values of n and h, the training of the TDNN parameters is done exploiting the Bayesian Regularization backpropagation method [16].

In this context, the role of the data sampling time T_s is important: its value must be sufficiently small to match the dynamics of interest. On the other hand, a too small T_s results in the need to

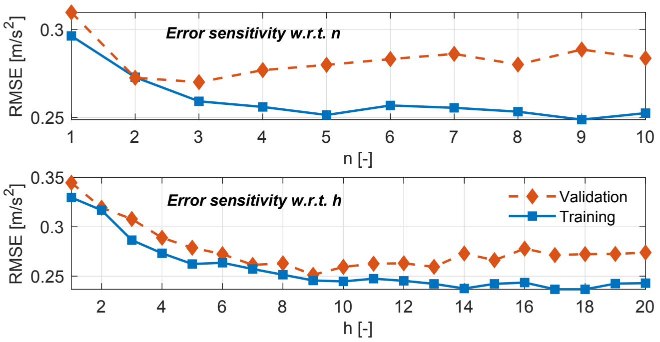


Fig. 3: Training and validation RMSE trend for increasing values of n and h, Driver 1.

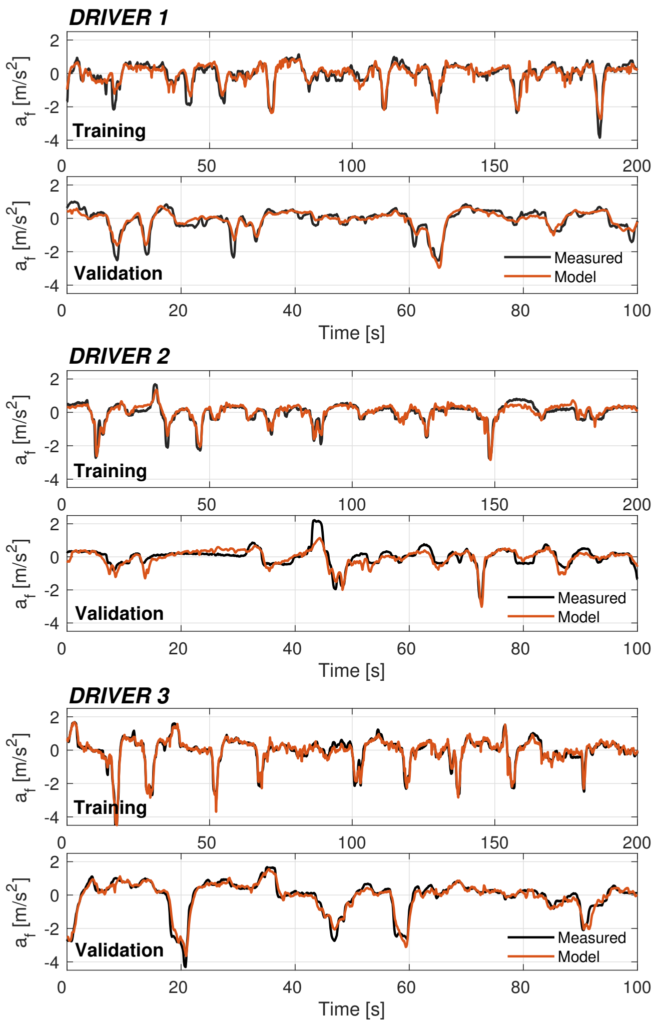


Fig. 4: Training and validation results for the three TDNN driver models, obtained fixing $n=3$ and $h=9$.

increase the value of h, so that the input time window is large enough (*i.e.* contains enough information) to compute the output value. Given that the typical human visual time response is in the order of magnitude of 200-300 $[ms]$, the dataset signals have been sub-sampled to 10 $[Hz]$ ($T_s = 100$ $[ms]$) before training the network.

In order to fix the TDNN structure, the training and validation errors for different values of n and h are studied. Since a combined optimization of the two parameters would result into a complex non-linear optimization problem, a sequential two-steps approach is here followed. In the first step, the value of h is kept constant and different TDNN models are then trained for values of $n = 1,...,10$ and for each one of the three drivers datasets (for a total of 30 different models): for each model, validation and training Root Mean Square Errors (RMSE) are computed. In this phase, the value of h is set equal to 10, which implies that the driver takes actions based on the past 1 second, as the studies on the human perception and reaction time suggest. The training and validation errors, as functions of n, are depicted in the upper plot of Figure 3 for Driver 1. While the training error drops as n increases, the validation error shows the typical decreasing-increasing trend that indicates the model data overfitting for values of $n > 3$.

In the second step of the model order selection, the value of h is refined keeping n constant, equal to the previously found value. Training and validation errors as functions of h are represented in the bottom plot of Figure 3. In this case, the best value of the parameter which minimizes the validation error is found to be $h = 9$, close to the *a priori* value set in the first phase.
Such structure choice for the TDNN leads to an overall number of 67 degrees of freedom (network parameters) for the model itself. The same training and order selection procedure is applied for Driver 2 and 3 models, leading to practically identical results.

C. Driver modelling results

The performance of the trained models are assessed in terms of validation errors on the respective validation datasets. Firstly, each model effectiveness is verified on its own driver dataset. In Figure 4, training and validation results are shown. As can be noticed, the output acceleration $a_f(t)$ of the TDNN models matches with good approximation the behaviour of the drivers in both cases.

It is also interesting to analyse how each model behaves when trying to explain the driving style of a different driver. This check allows to highlight the specificity of each driver behaviour, that cannot be generically described by a single model. The results of such cross-test are reported in Table I by means of RMS error values on validation data. For each driver, the best modelling results

Validation Data	RMSE $[m/s^2]$		
	Model #1	Model #2	Model #3
Driver #1	**0.25**	0.27	0.30
Driver #2	0.49	**0.33**	0.44
Driver #3	0.39	0.41	**0.25**

TABLE I: Driver TDNN models performance on training and validation datasets of the unseen drivers.

are obtained with its respective model (as expected). Moreover, the use of different model leads to a non negligible performance loss (ranging from 8% to more than 50%). This confirms that, despite the structure of the TDNN being the same ($h=9$, $n=3$), the model parameters must be different for each driver, and that the proposed modelling is capable of capturing their driving style differences.

To conclude the model identification discussion, in Figure 5 a comparison between the performances of the identified TDNN model and a second order linear one (as suggested in [14]) are shown, on the training set of Driver 2. In particular, it can be noticed how the linear model is not capable, by construction, of differentiating the acceleration from the braking manoeuvre, leading to poor RMS fits.

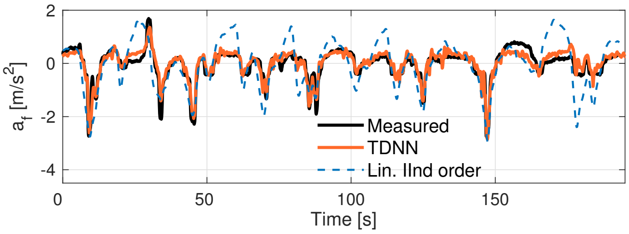


Fig. 5: Modelling performances of the identified TDNN and a linear II order dynamic model, as suggested in [14].

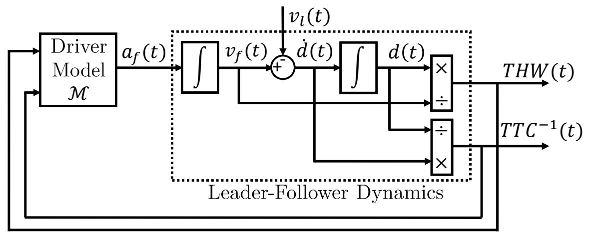


Fig. 6: Block diagram of the closed-loop simulation setup.

IV. ACC-ORIENTED DRIVER MODEL ANALYSIS

As discussed in Section II-C, the drawback of using a Neural Network model is the complexity in its parameter interpretation and feature extraction, due to the high number of degrees of freedom. Thus, to extract relevant features for an ACC-oriented driving style classification, each driver model is analysed in a simulated car following scenario. It should be stressed that the simulation approach proposed does not imply any ideality or constraint on actual implementation of the method: the driver behaviour is analysed in the natural closed-loop scenario it is meant to describe but the non-linearity of the model does not allow for any analytical study on its closed-loop behaviour.

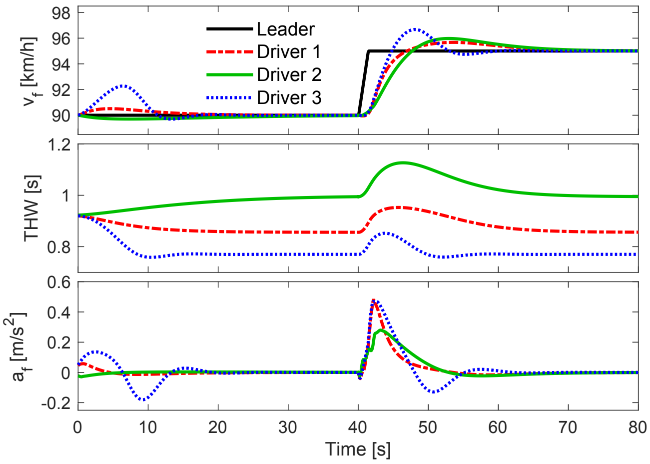
A. Simulation Setup

The block diagram of the simulation setup used for the trained models analysis is depicted in Figure 6: it reproduces the car following scenario (Figure 1) with some appropriate modifications.

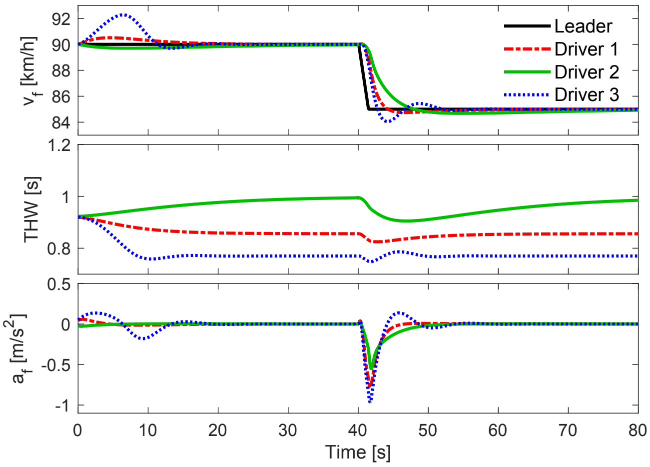
The FV Driver and FV Dynamics blocks are here substituted by the identified driver model, and the FV speed $v_f(t)$ is obtained by integrating the driver model output $a_f(t)$. The LV dynamics is reduced to the exogenous signal $v_l(t)$. The relative speed between FV and LV is computed by subtracting the two vehicle speeds $\dot{d}(t) = v_f(t) - v_l(t)$ and the relative distance $d(t)$ is obtained by integration. Finally, the $THW(t)$ and $TTC^{-1}(t)$ are calculated and their instantaneous values fed as input to the driver model, closing the control loop. In this setup, the LV speed $v_l(t)$ is used to perturb the Leader-Follower dynamics.

B. Closed-loop analysis and features extraction

To extract features for the characterization of each driver, their closed-loop system responses, as in Figure 6, are analysed. The simulation is initialized with $v_f(0) = v_l(0) = 90[km/h]$ and $d(0) = d_0 = 23[m]$ (the average speed and distance values registered during the experimental campaign). After the initial transitory is settled, a positive and a negative variation in the leader speed is applied. In order to mimic a realistic driving scenario, the absolute value of the leader acceleration has been limited to $1[m/s^2]$, equal for the acceleration and braking manoeuvre. The final steady-state



(a) Closed-loop response to positive variation of $v_f(t)$.



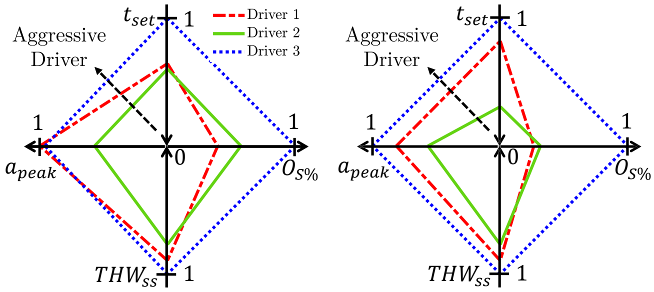
(b) Closed-loop response to negative variation of $v_f(t)$.

Fig. 7: Simulated responses of the closed-loop systems.

speed value v_{l_F} of the LV has been limited, to keep all the simulated variables within the experimentally observed ranges. Indeed, since we are dealing with non-linear models, results change quantitatively for different v_{l_F} values; nevertheless the considerations that can be derived from the following analysis still hold.

The results of such simulations are shown in Figure 7a and 7b. The inspection of the first transient (common to both scenarios) allows to draw some initial considerations on the responses. It is interesting to notice how the three drivers transitorily modify their speed to match different values of Time Headway, compatible with the expected driving aggressiveness: smaller THW for Driver 3, and higher for Driver 2. It should be remarked that while training the model no specific information about the steady-state Time Headway has been explicitly included, pointing out the effectiveness of the modelling approach in learning the driver style.

The analysis of the responses *w.r.t.* leader speed changes shows how all the identified driver models react to the perturbation, adapting the value of the $v_f(t)$ accelerating/braking so that, after a transient, it corresponds to the final value v_{l_F} of the LV speed. The transient behaviour however, varies from model to model and differs in the two cases of positive and negative variations of $v_f(t)$. Furthermore, notice that the steady-state value of the Time Headway settles on the same value prior to the perturbation, proving the driver model capability of adapting the value of



(a) Positive $v_f(t)$ variation.

(b) Negative $v_f(t)$ variation.

Fig. 8: Spider plots of the drivers features, normalized *w.r.t.* the value corresponding to the most aggressive driving style. Arrows indicates direction of growth of the features.

the safety distance $d(t)$ according to the absolute vehicle speed $v_f(t)$. Finally, the comparison between acceleration and breaking cases allows for another interesting consideration: in the braking case the driver closed-loop performance is better, with a smaller settling time and overshoot, at the cost of a higher vehicle absolute acceleration. This reflects, on the one side, the already discussed higher vehicle longitudinal dynamic performance in the breaking case. On the other, this result can be nicely interpreted as a generally higher attention and care of the driver in avoiding collisions with the preceding vehicle - which are possible when the leader vehicle brakes if no action is taken by the follower.

In light of the simulation results, four different features has been selected, which carry useful information about the driving style matched by the models. Firstly, the settling time of the FV speed $v_f(t)$ response t_{set}, defined as the time instant after which the following condition holds:

$$|v_f(t_{set}+\tau)-v_{l_F}| < 0.02\cdot|v_{l_F}-v_{l_I}| \forall\tau\geq 0 \tag{3}$$

The smaller the value of t_{set}, the more responsive/aggressive is the driving style. Then, the percentage overshoot $O_{S\%}$ of the $v_f(t)$ response with respect to the final value of the LV speed v_{l_F}. Greater values of $O_{S\%}$ indicate a more aggressive behaviour. As third, the steady-state Time Headway value THW_{ss}. The smaller the value of such feature, the more aggressive is the driver behaviour, as suggested by [5]. Finally, the acceleration peak value $a_{peak} = max|a_f(t)|$, that represents the maximum control action required to adjust the FV speed. The higher the value of a_{peak}, the more aggressive is the driver behaviour. The normalized features values, computed over the simulated responses, are represented using spider plots in Figure 8b. Notice that, for a better graphic yield, the axis of the settling time t_{set} and the percentage overshoot $O_{S\%}$ have been reversed. From the spider plots, it can be seen how Driver 3 shows the most aggressive behaviour, as pointed out by the values of all features. Nevertheless, also Driver 1 could be classified as aggressive, if one would inspect only the maximum acceleration (especially for the acceleration case). Focusing now on Driver 1 and 2, the former shows a more reactive behaviour in terms of settling time and peak acceleration, along with a greater aggressiveness (higher value of THW_{ss}). However, it can be seen how the overshoot of the latter driver reverses this trend, both during the acceleration and braking manoeuvre.

The discussed analysis allows to highlight the effectiveness of the proposed features in describing different facets of human driving behaviours: for a better personalised ACC experience several aspects - sometimes conflicting in terms of driving style binary classification - should be taken into account.

V. Conclusions

In this paper a driving style features extraction procedure is presented, meant to be used for the choice of an ACC controller configuration that best fits the driver road behaviour. A two-step approach is followed: in the first one a non-linear TDNN black-box model, is employed to learn the driver behaviour yielding excellent modelling results on real data. To compare the different driver models, as a second step, a closed-loop analysis is done in a simulated car following scenario. In particular, four features that characterize the drivers' style are isolated: their analysis is consistent with the expected driver behaviour, and allows for a faceted and non-trivial description of his/her driving style, leading to a possibly better personalization of the ACC tuning.

Future work will be devoted to repeat the TDNN training procedure when the FV is lead by an ACC controller, thus identifying a model for every ACC parametrization. Exploiting the discussed features extraction procedure, it will be possible to characterize each ACC setting and test the subjective matching of the closest tuning *w.r.t.* each driver style.

References

[1] L. Xiao and F. Gao, "A comprehensive review of the development of adaptive cruise control systems," *Vehicle System Dynamics*, vol. 48, no. 10, pp. 1167–1192, 2010.

[2] J. Bengtsson, *Adaptive cruise control and driver modeling*. Department of Automatic Control, Lund Institute of Technology, 2001.

[3] A. Vahidi and A. Eskandarian, "Research Advances in Intelligent Collision Avoidance and Adaptive Cruise Control," *IEEE Intelligent Transportation Systems Magazine*, vol. 4, no. 3, pp. 143–153, 2003.

[4] C. Marina Martinez, M. Heucke, F. Y. Wang, B. Gao, and D. Cao, "Driving Style Recognition for Intelligent Vehicle Control and Advanced Driver Assistance: A Survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 3, pp. 666–676, 2018.

[5] E. De Gelder, I. Cara, J. Uittenbogaard, L. Kroon, S. Van Iersel, and J. Hogema, "Towards personalised automated driving: Prediction of preferred ACC behaviour based on manual driving," *IEEE Intelligent Vehicles Symposium, Proceedings*, vol. 2016-Augus, no. Iv, pp. 1211–1216, 2016.

[6] M. Brackstone and M. Mcdonald, "Car-Following-Historical-reiview.pdf," *Transp. Res. F*, vol. 2, no. 1999, pp. 181–196, 2000.

[7] J. Wang, L. Zhang, D. Zhang, and K. Li, "An adaptive longitudinal driving assistance system based on driver characteristics," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 1, pp. 1–12, 2013.

[8] S. Lefevre, A. Carvalho, and F. Borrelli, "Autonomous car following: A learning-based approach," *IEEE Intelligent Vehicles Symposium, Proceedings*, vol. 2015-Augus, no. Iv, pp. 920–926, 2015.

[9] S. Lefèvre, A. Carvalho, Y. Gao, H. E. Tseng, and F. Borrelli, "Driver models for personalised driving assistance," *Vehicle System Dynamics*, vol. 53, no. 12, pp. 1705–1720, 2015.

[10] S. Lefèvre, A. Carvalho, and F. Borrelli, "A learning-based framework for velocity control in autonomous driving," *IEEE Transactions on Automation Science and Engineering*, vol. 13, no. 1, pp. 32–42, 2016.

[11] M. Kuderer, S. Gulati, and W. Burgard, "Learning driving styles for autonomous vehicles from demonstration," *Proceedings - IEEE International Conference on Robotics and Automation*, no. June, pp. 2641–2646, 2015.

[12] F. Simonelli, G. N. Bifulco, V. De Martinis, and V. Punzo, "Human-like adaptive cruise control systems through a learning machine approach," pp. 240–249, 2009.

[13] X. Chen, Y. Zhai, C. Lu, J. Gong, and G. Wang, "A learning model for personalized adaptive cruise control," *IEEE Intelligent Vehicles Symposium, Proceedings*, no. Iv, pp. 379–384, 2017.

[14] J. Lu, D. Filev, and F. Tseng, "Real-time Determination of Driver's Driving Behavior during Car Following," *SAE International Journal of Passenger Cars - Electronic and Electrical Systems*, vol. 8, no. 2, 2015.

[15] A. Waibel, T. Hanazawa, G. Hinton, K. Shikano, and K. J. Lang, "Phoneme Recognition Using Time-Delay Neural Networks," *IEEE Transactions on Acoustic, Speech and Signal Processing*, vol. 37, no. 3, pp. 328–339, 1989.

[16] D. J. C. MacKay, "Bayesian Interpolation," *Neural Computation*, vol. 4, no. 3, pp. 415–447, 2008.