Comparison of Direct and Indirect Identification of a Human Driver Model

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***Abstract*—This paper focuses on recent advancements in the identification of human dynamics in vehicle steering tasks. The field of human driver identification encompasses a plethora of distinct models and methods for parameter identification. This study experimentally compares the most prominent identification approaches in terms of model efficiency (ME). The advantages of indirect identification methods are theoretically discussed and experimentally verified using a dataset comprising extensive measurements from 23 individual drivers. Both theoretical analysis and numerical evaluation of ME corroborate that the indirect identification method proposed by the author is superior to the direct methods employed in many previous studies. The suggested approach is expected to provide a more reliable estimate of drivers' dynamic parameters, which are desirable for further statistical analyses or machine learning applications in this research domain.**

***Index Terms*—cross-validation, driver behaviour, identification, model, simulator, steering control.**

I. Introduction

The author's previous work predominantly focused on establishing the optimal model structure for modelling human actions in various control tasks [1]–[4]. However, even with the selection of an optimal model structure, the effectiveness of data processing hinges on the proper selection of the identification method. This paper aims to compare and evaluate two primary approaches to identifying a human operator's dynamic model during car driving scenarios.

In our scenario, the human driver controls a simulated vehicle on a straight highway, where the driver must change lanes according to instructions while maintaining a constant vehicle velocity. This setup allows for a controlled environment to assess the identification methods accurately.

The paper is structured as follows. Section II reviews the theoretical fundamental differences between the direct and indirect identification methods for obtaining the model of human dynamics. Practical illustrations are referenced whenever possible to avoid a purely theoretical discussion. Section III details our experimental setup, the model structures used in this study, and the process of their evaluation in terms of model efficiency (ME). Section IV provides a practical demonstration of our theoretical considerations, showing that the indirect identification method, despite its added complexity, yields more accurate models with higher ME.

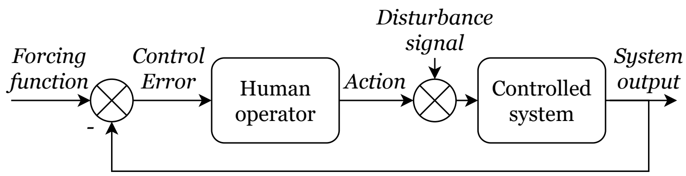

Fig. 1. Simple feedback loop describing human operator as a control element.

II. Related work

A human driving a vehicle assumes the role of a controller. Many researchers aim to develop a mathematical description of this human controller. The transfer function or non-linear model of this controller is unknown and requires parameter identification. The initial step typically involves selecting the model structure, followed by the identification of its parameters. Once the model structure is chosen, a decision on the identification approach must be made. The two identification methods analysed here are direct and indirect identification.

A. Direct (open-loop) identification

Identification in an open-loop is conducted when the driver model is treated as if it were disconnected from the control loop. Only the controller's input and output signals are utilised for the identification of the model parameters. The simulated controller output does not influence its inputs via the response-controlled system; instead, the measured inputs of the controller are used. In the simplest case, the input signal is the control error, and the output signal is the driver's action, specifically the angle of the steering wheel (see Fig. 1).

The first issue with such identification arises here. Evidently, these input and output signals are not independent of each other. When the driver model is within the control loop, the driver's action eventually (after passing through the controlled plant) affects the control error, and this feedback is not accounted for in the open-loop identification.

This grave issue has been previously described by [5] and later by [6], who indicate that a direct identification approach based solely on input and output signals may, in cases where the control error signal remains close to zero for extended periods, likely result in a model biased towards the inverse of the controlled plant's dynamics.

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In extreme cases, such an identification process can result in a superfluous model that provides accurate steering actions in response to measured control errors but becomes unusable during closed-loop simulation. An example of this is the non-linear fuzzy model in [7], which exhibits negative gain for small values of the control error. This means that in a closed loop, it behaves as a "destabiliser" and forces the car away from the centre of the driving lane. Yet, in the open loop, the same model can approximate the measured response very well.

This outcome was probably caused by an inappropriate selection of the driver model and learning data, where only one "average" lane change was used for identification rather than the entire experiment consisting of several lane change actions distributed over time. The single lane change signal does not have a high enough order of persistent excitation to fully identify the chosen model, as described in detail by classical identification textbooks [8].

Despite these issues, this identification approach is still widely used. Its implementation is much simpler compared to the closed-loop identification method, as it only requires defining the identified driver model. With careful data and model selection, reasonable results can be obtained. Such research can be found, for example, in [3], [9]–[12].

B. Indirect (closed-loop) identification

Conversely, the indirect, or closed-loop, identification method involves modelling the entire system (as shown in Fig. 1). This includes the human driver model, the controlled system dynamics, and the structure of the loop, detailing how these subsystems are interconnected.

With this method, the plant's dynamics may be identified, but the process is simplified when it is known in advance. Once the entire closed-loop model is identified, the parameters of the human driver controller can be extracted.

This approach also allows for the identification of a greater variety of driver models, such as multi-input controllers. For example, in [4], the analysed modified multi-loop Donges model [13] requires a vehicle's heading signal as an input. Despite the fact that this signal is not measured in the experiment, such a model can be identified in the closed loop since the unmeasured signal can be obtained via modelling the controlled vehicle's dynamics in the loop.

III. Experiment description, selected driver model and its evaluation

In this section, the description of the experiment is presented along with the selected human driver model and mathematical evaluation of its prediction capabilities.

A. Experiment description

The two identification methods were evaluated through a series of tests in which the driver had to change lanes on a motorway according to instructions. Each driver participated in four experiments, differing in the power of disturbance signal present.

Fig. 2. Vehicle driving simulator screenshot showing a typical test scenario. [4]

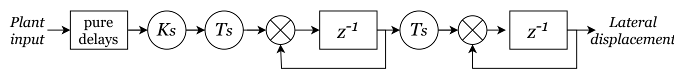

Fig. 3. Vehicle dynamics diagram.

These experiments were the same as those described in [4]: (1) measurement without disturbance, (2) and (3) measurements with white noise disturbance signals filtered by 4th and 2nd order filters respectively, and (4) measurement with a filtered pseudo-random binary sequence (PRBS) disturbance signal filtered by a 4th order filter. This article analyses the same measured data, but the dataset was extended to 23 individual drivers.

The study utilised an existing vehicle driving simulator, originally developed by [10] and later extended and modified by [4] to include disturbance signals. The vehicle driving simulator consists of a computer with a steering wheel and pedals as inputs to control the simulated vehicle. The simulator runs an application created in the Unreal Engine framework, which simulates the vehicle and its surroundings and logs all necessary data for further signal processing.

The controlled plant is modelled as a vehicle with the transfer function

$$F_{\mathrm{S}}(z) = K_{\mathrm{S}} T_{\mathrm{S}}^2 \frac{z^{-2}}{(1-z^{-1})^2} z^{-d_{\mathrm{s}}}, \tag{1}$$

which is represented by two discrete integrators with a delay $d_{\mathrm{s}} = 40$ and a gain $K_{\mathrm{S}} = 73$. The continuous equivalent would be, assuming zero-order hold, a double integrator with gain and delay with transfer function $F_{\mathrm{Sc}}(s) = K_{\mathrm{Sc}} \cdot \mathrm{e}^{-\tau_{\mathrm{S}} s}/s^2$. The sampling period $T_{\mathrm{S}} \approx 7$ ms was taken as an average sampling period of all recorded samples. This adjustment was necessary due to slight sampling non-uniformity in the vehicle simulator.

The corresponding diagram of the vehicle model represented by this equation is depicted in Fig. 3.

B. Identified driver model and its evaluation

In this paper, a 2nd order McRuer model

$$F_{\mathrm{R}}(s) = \frac{K_{\mathrm{R}} s}{T_{\mathrm{R}}^2 s^2 + 2\xi T_{\mathrm{R}} s + 1} \mathrm{e}^{-\tau s} \tag{2}$$

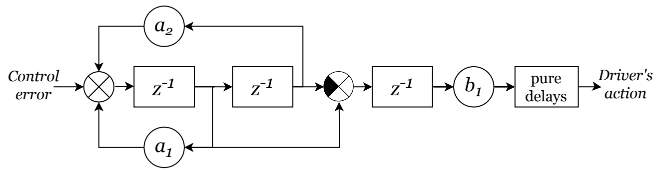

Fig. 4. 2nd-order McRuer model. [4]

is identified. Here K_{R} is the driver's gain, T_{R} is the time constant, ξ is the damping factor and τ is the response delay. Derived from the theory presented by McRuer [14], the same model was used as a linear component in the publications dealing with the same driving task [3], [9]–[12].

Since we are dealing with the discrete data, the zero-order hold equivalent

$$F_{\mathrm{R}}(z) = \frac{b_1(1-z^{-1})}{1-a_1z^{-1}-a_2z^{-2}}z^{-d_{\mathrm{r}}} \quad (3)$$

of the continuous model (2) is identified. Here d_{r} is the transport delay of the driver and a_1, a_2 and b_1 define the dynamics of the model. The scheme of the selected model is shown in Fig. 4.

It is important to note that this model appears to be inappropriate for scenarios with a higher intensity of the disturbance signal present, as discussed in [4]. However, that is a perfect opportunity to observe how the two identification approaches behave in cases of appropriate and inappropriate model selection.

To find the optimal parameters of the driver model to fit the measured data, the MATLAB function `ssest` was used. The models were identified in discrete state-space representation. For closed-loop identification, also the vehicle dynamics was taken into consideration, forming a closed loop with two inputs (forcing function and disturbance signal) and two outputs (control error and driver's action). For open-loop identification, only the driver model is identified with one input (control error) and one output (driver action).

To quantify the prediction capabilities of the models identified by direct and indirect method, a the standard cross-validation process is used, as described in [15], which divides the data into K folds. In this case $K = 2$ folds were used: $x_1(nT_{\mathrm{s}})$ and $x_2(nT_{\mathrm{s}})$. Two models are trained:

1) The first model is trained using fold $x_1(nT_{\mathrm{s}})$ and validated using the fold $x_2(nT_{\mathrm{s}})$.
2) The second model is trained using the fold $x_2(nT_{\mathrm{s}})$ and validated using the fold $x_1(nT_{\mathrm{s}})$.

This ensures that the performance of the model is tested on data that differ from the training data. ME on the validation fold is defined as

$$\mathrm{ME}_{\mathrm{Val_k}} = 1 - \frac{\sum_{n=0}^{N-1}[\hat{x}_k(nT_{\mathrm{s}}) - x_k(nT_{\mathrm{s}})]^2}{\sum_{n=0}^{N-1}[x_k(nT_{\mathrm{s}}) - \overline{x}_k]^2}, \quad k = 1, 2. \quad (4)$$

Here $x_k(nT_{\mathrm{s}})$ is the validation signal and $\hat{x}_k(nT_{\mathrm{s}})$ is the signal predicted by the model. The ME is clearly related to the mean squared error (MSE), which is proportional to the term in the nominator of (4). Higher ME values indicate better prediction capabilities of the model. The limit value ME = 1 is achieved only when the model prediction is identical to the validation data. Since there are two folds for which the MEs are evaluated, the mean value of both MEs was used for the evaluation, so $\mathrm{ME} = \frac{1}{2}(\mathrm{ME}_{\mathrm{Val_1}} + \mathrm{ME}_{\mathrm{Val_2}})$.

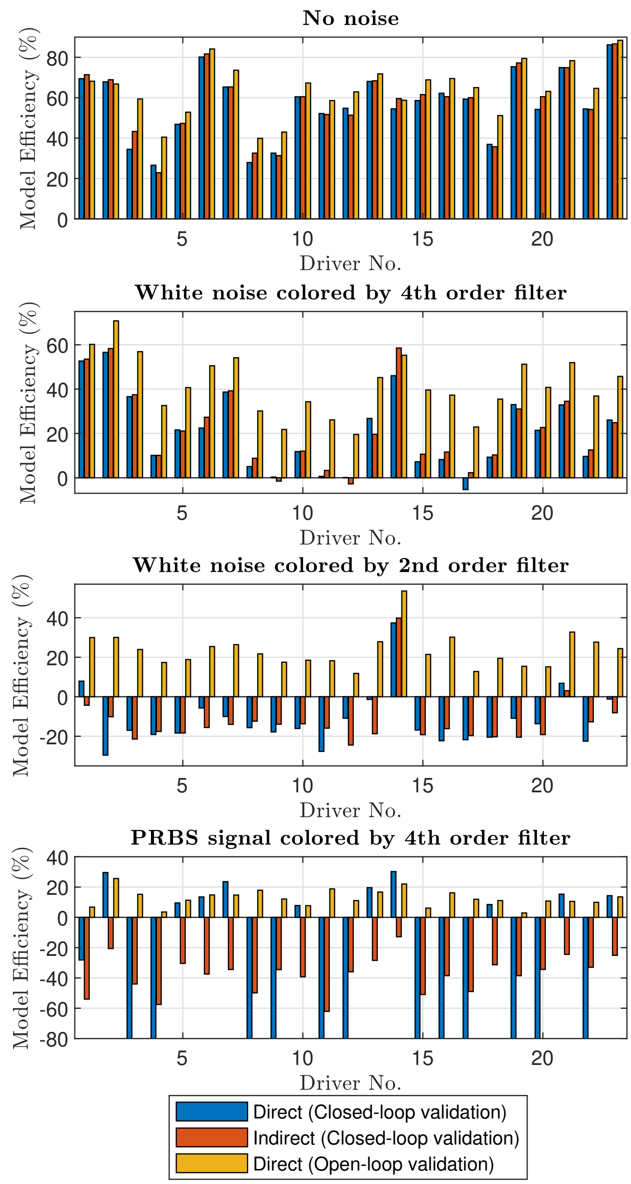

Fig. 5. Model efficiency on validation data for different identification methods during four different scenarios.

IV. Comparison of Direct and Indirect Identification on Measured Data

This section presents the results of the two identification methods tested on experimentally measured data. The discussion includes model efficiencies and the analysis of time series data.

A. Discussion on obtained model efficiencies

Fig. 5 presents bar graphs displaying the obtained MEs for the selected model, determined using two identification methods. For each measured driver and scenario, the ME value is illustrated for both the direct and indirect methods validated on closed-loop data (represented by blue and orange bars, respectively). Additionally, the ME value for the direct method validated on open-loop data is shown (yellow bars). Table I contains the mean values of the MEs obtained in the individual scenarios.

Both methods validated on closed-loop data resulted in similar ME values in the first tree scenarios. This suggests that both methods could be equivalent when the selected model can adequately represent human reactions.

However, a closed-loop validation needs to be used even with the direct identification approach. The same models identified with the direct method and validated on open-loop data resulted in significantly higher ME values, as can be seen in Fig. 5 and Table I. Thus, these MEs obtained via open-loop validation overestimate the model prediction quality in the experiment.

As was shown in [4], the selected model cannot adequately represent the reactions of human drivers in scenarios 3 and 4. This is consistent with the ME values validated in closed-loop both for direct and indirect identification method. However, as observed in previous scenarios, models obtained by a direct approach validated only on open-loop data resulted in much higher ME values, which do not represent the behaviour of the model in closed loop.

The differences become even more pronounced in the last scenario. Despite the fact that models identified by the direct identification method were all stable and resulted in positive MEs when validated on open-loop data, nearly half of the models obtained by the direct approach were unstable when simulated in the closed loop. In the last scenario, the MEs for the direct identification method validated in closed-loop fall significantly below the graph's y-axis, with unstable results as low as $-4 \cdot 10^{21}$ %.

On the other hand, models identified by indirect method always resulted in stable closed-loop behaviour, even when the selected model can not represent human driver reactions. However, it should be noted that when the direct method validated on closed-loop data does not fail in producing unstable closed-loop behaviour, the MEs in the last scenario tend to be higher (and even positive) than those of the indirectly identified models.

B. Evaluation from time series data

The outcome of the chosen identification approach can also be seen in the time series data shown in Figs. 6 and 7. The first subplot in these figures visualizes the forcing function (desired driving lane) and the actual vehicle's position as the driver deals with the task of getting and keeping the vehicle in the given driving lane. The second subplot compares measured data with the prediction of a model identified with a direct or indirect method validated in a closed-loop. The final subplot shows measured data alongside the predictions of a model identified using a direct method validated in an open-loop.

TABLE I
AVERAGE MEs IN INDIVIDUAL SCENARIOS

Scenario No.	Direct ME (Closed-loop validation) (%)	Indirect ME (Closed-loop validation) (%)	Direct ME (Open-loop validation) (%)
1	56.66	57.71	64.17
2	20.51	21.98	41.74
3	-11.59	-12.74	23.50
4	$-1.81 \cdot 10^{20}$	-37.67	12.67

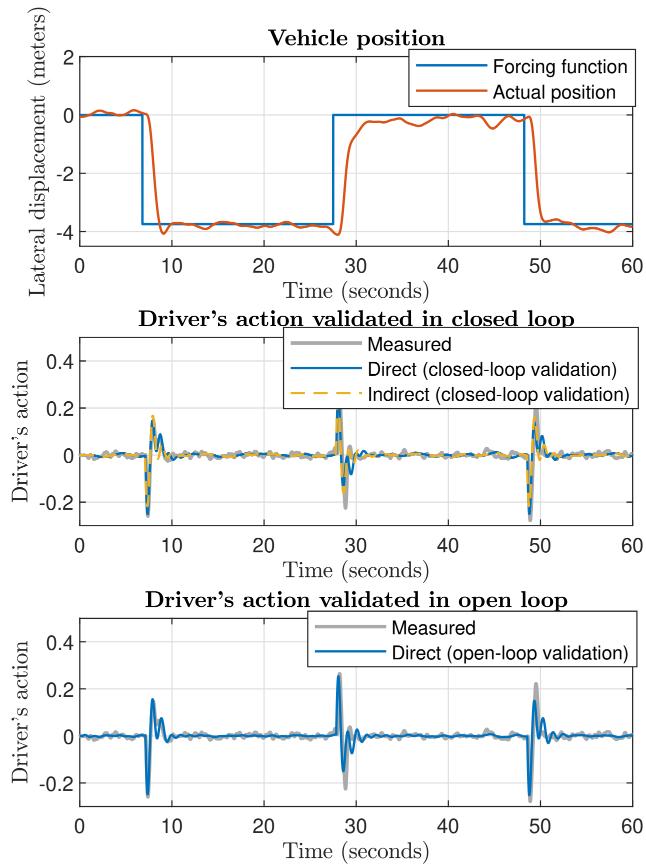

Fig. 6. Driver action – validation data and predicted signal waveforms for scenario 2.

Fig. 6 presents an example in which the results of the different identification methods were nearly indistinguishable. This case displays selected time periods for driver 14 in scenario 2. All identification approaches produced stable models in both closed-loop and open-loop validation. The model predictions closely approximate the validation data, with only minor differences among them.

Fig. 7 demonstrates a situation where the result of the direct identification method produced a stable model in the open loop, while the same model, when connected to the vehicle's dynamics in the closed loop, generated unstable results. The selected time data pertain to driver 11 in scenario 4. The second graph in Fig. 7 clearly shows that the output of the directly identified model in the closed-loop quickly turns

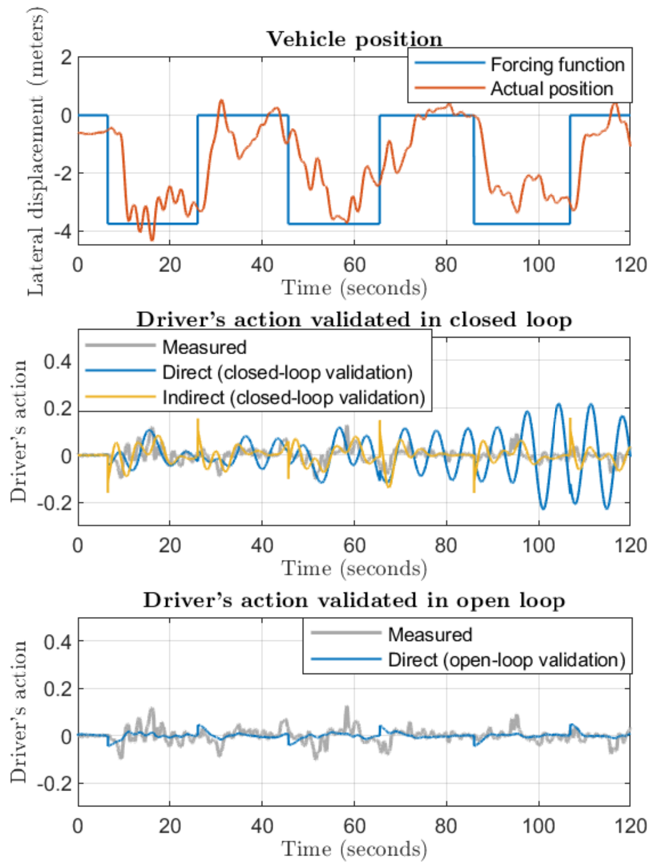

Fig. 7. Driver action – validation data and predicted signal waveforms for scenario 4.

into oscillations, with the magnitude increasing over time. Meanwhile, the predictions of this model simulated in the open-loop, as shown in the final graph in Fig. 7, exhibit no signs of unstable behaviour.

V. Conclusion

In this paper, an experimental study was conducted to evaluate the identification approach of a human driver model. A second-order transfer function model of a human driver was subjected to both direct and indirect identification processes and evaluated in both closed and open loops using a data set gathered from 23 different drivers.

The results show that using the direct identification method evaluated on open-loop data tends to overestimate the model's prediction capabilities and occasionally produces a model that is unstable when connected and simulated in the closed loop, yielding extreme negative values of ME.

Conversely, the indirect identification approach results in a more realistic estimation of the model's prediction quality. Moreover, indirect identification does not produce unstable models even when the selected model cannot adequately represent human action.

Based on the observed behaviour of the individual identification methods, the indirect or closed-loop identification method is recommended, especially in cases where the model of the controlled plant is known and can be easily employed in the model of a whole closed loop.

This result will enable the development of more accurate models of human dynamics. This will enhance the subsequent statistical evaluation of the tested drivers and allow for more precise predictions about the drivers using machine learning approaches.

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