Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

Rider model identification using dynamic neural networks

Paul LOISEAU * **Chaouki Nacer Eddine BOULTIFAT** *
Philippe CHEVREL * **Fabien CLAVEAU** * **Stéphane ESPIÉ** **
Franck MARS ***

* *IMT-Atlantique, LS2N UMR CNRS 6004 Nantes, France (e-mail: firstname.lastname@imt-atlantique.fr).*
** *Ifsttar, TS2/SIMU&MOTO, SATIE UMR CNRS 8029, Orsay, France (e-mail: stephane.espie@ifsttar.fr).*
*** *Centrale Nantes, CNRS, LS2N UMR CNRS 6004 Nantes, France (e-mail: franck.mars@ls2n.fr).*

Abstract: Car driver modeling is a well-known research topic, with significant existing contributions. In contrast, important questions related to motorcyclist modeling remain unanswered. This study focuses on identifying a motorcyclist model that can predict the steering angle and the rider roll angle. A black box rider model in the form of a time delay neural network is presented. This model was developed using experimental data recorded with an instrumented motorcycle from the VIROLO++ research project. It is used for three main issues. First, the selection of input signals and their impact on prediction performance is discussed. Next, the model's ability to predict the behavior of a variety of motorcyclists is demonstrated. Finally, the nonlinearity of the model is analyzed. These results pave the way to the development of a cybernetic rider model.

Keywords: Motorcycle rider modeling, Cybernetic rider model, Identification, Time delay neural network.

1. INTRODUCTION

Year after year, motorcyclists remain one of the most vulnerable groups of road users. According to the french observatory of road safety (ONISR), in France in 2018, the risk of being killed was 22 times higher for a motorcyclist than for a car driver, making motorcycles an ongoing central issue of road safety. Outside urban areas, 42% of lethal accidents involving motorcycle happen along road bends. This observation was one of the motivations behind the VIROLO++ research project (Espié et al., 2016). The main objective of this project is to provide a better understanding of rider behavior along bends in order to propose efficient learning or prevention tools. The project has three main objectives. The first is to develop a better understanding of the rider/motorcycle interaction and of rider modeling. The second involves designing a risk function for bend taking, and the third is the precise reconstruction of motorcycle trajectories. All of these tasks rely on road tests with an instrumented motorcycle (as presented in Section 3.1).

The present paper, which is part of the rider modeling task, adresses three important considerations. The first is the choice of input signals to obtain satisfying prediction capacities. Once appropriate results are obtained for a rider, the second issue is determining whether the model has sufficient richness to reproduce the behavior of a variety of riders. Finally some model characteristics are analyzed, especially nonlinearity.

The paper is organized in four main parts. Section 2 summarizes the state of the art of rider modeling and outlines the assumptions made in this paper. Section 3 presents the experiments conducted as part of the VIROLO++ research project. Section 4 discusses the identification problem, specifically the choice of the rider model inputs and outputs and the motivation behind using a time delay neural network (TDNN). Finally, Section 5 analyzes the results obtained with the presented approach, and individually addresses the three previously mentioned objectives of the paper.

2. RIDER MODELING

Before the experiment and the modeling problem are presented, this section summarizes the existing literature on motorcyclist modeling and presents the main assumptions of the paper.

2.1 State of art

A motorcycle is an unstable system with significant roll dynamics. The mass ratio between the vehicle and the driver is also very high. This makes motorcycle driving more complex than, for instance, car driving. As a consequence, rider modeling is difficult and remains a significant research challenge.

⋆ This project was supported by the VIROLO++ project funded by Agence Nationale de la Recherche (ANR-15-CE22-0008-02).

A significant portion of literature on rider modeling covers the mechanical influence of the rider body as part of the global dynamic system: motorbike and rider. This paper focuses more on the rider driving task and the associated processing of sensory information. In this context, the literature about motorcycle riding deals either with rider observation or rider modeling. A general overview of this work is given in (Popov et al., 2010; Kooijman and Schwab, 2013). In the domain of rider observation, the main addressed topics are handlebar control (steering torque *vs.* steering angle), the prevalence of different forms of control (handlebars *vs.* rider lean) (Zellner and Weir, 1978; Rice, 1978; Bocciolone et al., 2007) and the differences between experienced and novice riders (Rice, 1978; Prem and Good, 1983; Evertse, 2010). The conclusions vary depending on the considered maneuver, but in general, novice rider behavior is more subject to interpersonal variations. Moreover, experienced riders are more reactive and able to uncouple handlebar actions and body lean. The handlebars are considered the most efficient means of controlling the motorcycle. This importance may vary according to the speed. Finally, most papers conclude that a human rider controls a motorcycle by applying a steering torque rather than a steering angle.

The literature on rider modeling can be divided into two groups: human rider modeling and automatic control. The articles on human rider modeling (Weir, 1972, 1973; Prem and Good, 1984) are mainly based on a theoretical approach and are not necessarily validated with experimental data. The proposed models in (Weir, 1972, 1973) have three inputs (the motorcycle roll angle, the heading angle and the lateral position) and two outputs (the steering torque and the rider lean angle). The internal structure of the model comprises three nested loops. The speed dependence is not explicitly formalized. (Prem and Good, 1984) have used a similar model adapted to novice riders. The automatic control based literature (Sharp, 2006, 2007; Katayama et al., 1988; Mammar et al., 2006) replaces the human rider with a controller. The conclusions of (Katayama et al., 1988) indicate that the handlebar steering torque is the main method used to control a motorcycle. (Sharp, 2006, 2007) has analyzed the preview distance needed as a function of the speed and has concluded that a greater preview distance is required for motorcycle driving than for car driving. Furthermore the preview distance needed to control a motorcycle increases more than proportionally to the speed.

Although it is not exhaustive, this brief overview of the available literature demonstrates that cybernetic modeling of a motorcyclist is still an unsolved problem. The literature on car driver modeling and on aircraft pilot modeling may constitute important sources of inspiration, in particular concerning human perception.

Car driver modeling mainly involves visual and haptic perception. When one considers visual feedback, it is commonly accepted that a driver simultaneously uses both distant visual cues, to anticipate changes in road curvature, and near visual cues, to compensate for lateral position errors (Donges, 1978; Land and Horwood, 1995; Frissen and Mars, 2014). To formalize this dual process, two indicators are generally used to reproduce the human visual perception. In (Salvucci and Gray, 2004; Saleh et al., 2013), these two indicators take the form of two angles named θ_{near} and θ_{far} (they are illustrated in Figure 5). The haptic feedback along bends takes the form of a torque felt by the driver when interacting with the steering wheel. This torque involves the auto-alignment torque, as formalized in the cybernetic model proposed by (Saleh et al., 2013).

In a simplified model of a car driver, the role of vestibular feedback can be neglected. The same is not true for an aircraft pilot model, in which rotation dynamics and inclination with respect to gravity must also be considered. Pilot models, including those used for the design of flight simulators, therefore explicitly represent the properties of vestibular organs (Hosman, 2009; Lone and Cooke, 2014). Motorcycle modeling shares elements of both car driver modeling (both have similar visual control of trajectory) and aircraft pilot modeling. The dynamics of movement are more constrained in a motorcycle than in airplanes, but it is difficult to ignore the control of leaning in the motorcyclist model.

2.2 Paper assumptions

Creating a cybernetic rider model, that is, a dynamic model that explicitly describes a human rider's behavior through this model's structure and the meaning of its parameters, is an open problem. A possible high level description of such a model is given in Figure 1. The model incorporates three types of feedback used by a human rider to control a motorcycle: visual feedback, vestibular feedback and haptic feedback. Methods used by the rider to control the lateral motion of their motorbike are also described: handlebar manipulation (steering torque) and the generation of a roll torque. A first level of the model structure is also provided that involves two control processes: sensorimotor coordination and neuromuscular control. Describing each feedback signal and the content of the two control blocks precisely is the final goal of the rider identification work. However, comprehensive modeling can only be achieved gradually. The present paper summarizes only the initial step of this modeling process.

Although a cybernetic rider model should be derived from experimental data measured under real driving conditions, working with a motorcycle simulator may be considered as an alternative data collection method. Unfortunately, in reality, such a simulator is not as "easy" to build as, for instance, a car simulator (mainly because of the roll degree of freedom); hence, a motorcycle simulator is not the best approach for human rider modeling. Experiments on an instrumented motorcycle were made possible in this work through the VIROLO++ research project. In this project, a fully instrumented motorcycle (presented in Section 3.1) was developed and used to collect data for human driver observation and modeling.

As previously mentioned, deriving a cybernetic model directly from the experimental data gives rise to numerous questions especially pertaining to model structure and identifiability. The present paper does not address all of these questions at once, but focuses on three important considerations: the choice of appropriate input and output signals, the model's capacity to reproduce the behavior of a variety of riders and an analysis of the main characteristics

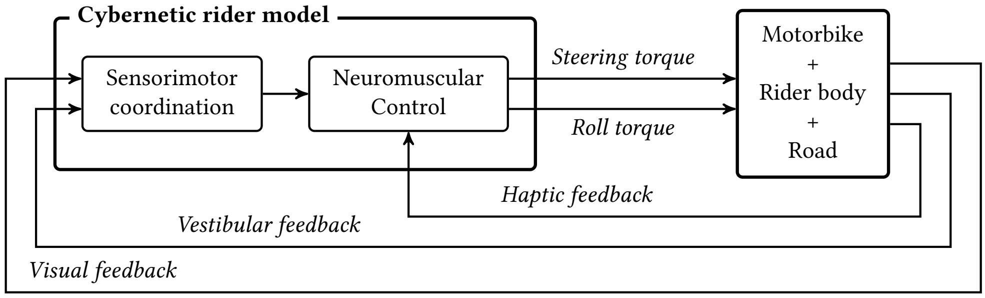

Fig. 1. Cybernetic rider model

of the model, in particular its nonlinearity. To investigate these questions, the rider model has been defined as a time delay neural network. Further details on this type of model are given in Section 4.3. This type of model has been chosen due to its capability to approximate a large class of nonlinear systems. This capability allows the model to describe nonlinear behavior, without *a priori* specification of one particular internal model structure. For instance, prior assumptions about relationships between the model's dynamics and the longitudinal speed can thus be avoided.

3. THE EXPERIMENT

This section describes the experiment conducted under real conditions with an instrumented motorcycle on a track. The motorcycle is presented first, followed by the road tests and the experimental data recorded.

3.1 The instrumented motorcycle

The instrumented motorcycle is presented in Figure 2. It is a Honda CBF1000. Most of the sensors are presented in the picture. The most useful sensors for the present paper are the GPS RTK, for trajectory recording; the motorcycle inertial measurement unit (IMU), for measuring the roll angle; the steering angle sensor and the speed sensor. Finally three IMUs placed on the rider (not visible in Figure 2) are also used to measure the rider roll motion.

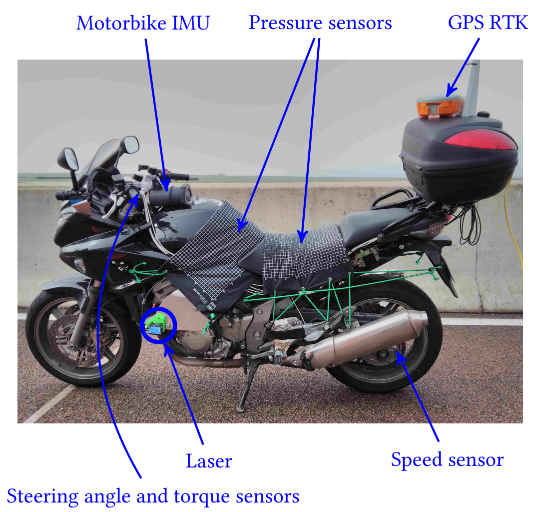

Fig. 2. The instrumented motorbike (VIROLO++ project)

3.2 The road tests

The road tests were conducted on a track (presented in Figure 3). The riders were novice riders of the French military force. Data from six riders are considered in this article. Each driver was asked to drive several laps without any driving instruction (normal driving). Of these laps of normal driving, one was used in the following experiment for the identification (or the neural network training) and a second lap was used for validating the prediction performance of the identified model.

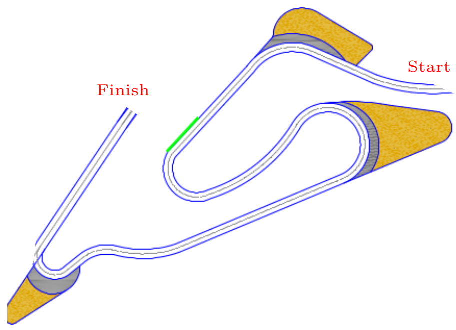

Fig. 3. Track used for the experiment

3.3 Experimental data description

The data from the experiment consist of the measures from all the sensors placed on the motorcycle and the rider from all laps of all riders. All signals were synchronized while recording and were sampled every 0.1s. Most data contained some high frequency noise and required filtering. In this paper all the data were manipulated off-line, so noncausal filtering was used to avoid introducing phase changes. Some additional pretreatments and estimations were needed to determine the rider input and output signals. These are briefly discussed in Section 4.1 but are not fully presented for readability and conciseness.

4. THE TDNN IDENTIFICATION PROBLEM

Based on the assumptions made in Section 2.2, this section presents the identification problem. First, the selection of the input and output signals of the rider model is detailed in Section 4.1, then the identification approach is presented in Section 4.2. Finally the identification process and the model characteristics are described in Section 4.3.

4.1 Rider model input and output signals

Before the model characteristics are discussed, the input and output signals considered for the rider model must be defined. As described in Figure 1, three types of feedback can be used by a human rider to control the lateral motion of a motorcycle. One source of information used by a rider to control a motorcycle comes from haptic feedback. On a motorcycle, as in a car, the rider applies a torque on the actuator and feels a torque response from the steering system. This haptic feedback directly interacts with the neuromuscular system in a closed loop. It is essential to carefully control the handlebars and this control results in a steering angle. Only the steering angle will be taken into account for the model since only the sum of the driver's torque and the steering column torque, and not the proper force feedback, can be measured on the instrumented motorcycle. Thus as indicated in Figure 4, only two types of feedback are considered in this paper: the visual feedback and the vestibular feedback. Two methods of control are considered: the steering angle (denoted δ in the following paragraphs) and the roll moment generated by the rider with their upper body.

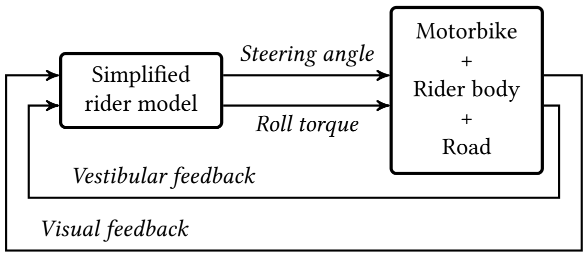

Fig. 4. Simplified cybernetic rider model

The hypothesis of this study concerning visual feedback is that the analysis of the visual scene conducted by a motorcycle rider is very similar to that of a car driver. Consequently, the same visual indicators have been selected. These indicators are the two angles presented previously θ_{near} and θ_{far} (Saleh et al., 2013). As illustrated in Figure 5, θ_{near} is the angle between the heading of the motorcycle and the near point, while θ_{far} is the angle between the heading and the tangent point. The near point is used to monitor the lateral position and to maintain a central lane position. It is placed in the center of the lane, 5 m ahead of the vehicle. The tangent point is used to anticipate the upcoming road curvature. Such indicators are not directly measured on the instrumented motorcycle, but are instead estimated from the trajectory measurements.

Vestibular feedback is used by the human rider to assess linear (translation and tilt) and rotational accelerations via the otoliths and the semi-circular canals, respectively. This feedback is consequently closely related to the motorcycle roll motion. In the present paper, the roll angle of the motorcycle θ_{rm} is considered as a possible input of the rider model. $\dot{\theta}_{rm}$ could also be considered, although the present paper does not directly consider it for simplicity. However the neural network model presented in Section 4.3 can estimate this signal if necessary.

The methods of control must also be considered. The first is the steering angle δ. The second (which is generally considered secondary to handlebar control) involves initiating

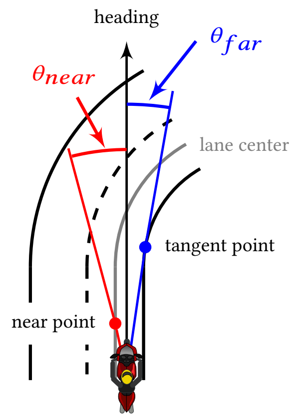

Fig. 5. Angles θ_{near} and θ_{far}

a roll torque with the upper body. This additional method of control is considered in the rider model using the rider roll angle θ_{rr} as second output.

The rider model used in this work is summarized in Figure 6. The inputs considered are the near angle θ_{near}, the far angle θ_{far} and the roll of the motorcycle θ_{rm}. The outputs considered are the steering angle, δ, and the rider roll angle, θ_{rr}. The longitudinal speed v_x constitutes an additional model input, as it certainly affects the rider model dynamics. These lists of input and output signals is validated with regard to the identification results in Section 5.1.

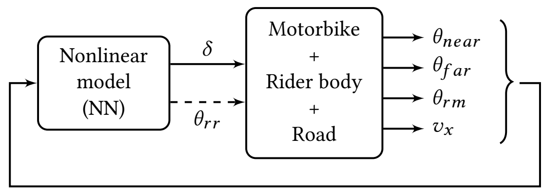

Fig. 6. Considered rider model

Examples of experimental output signals are given in Section 5 and some input signals are shown in Figures 7 and 8.

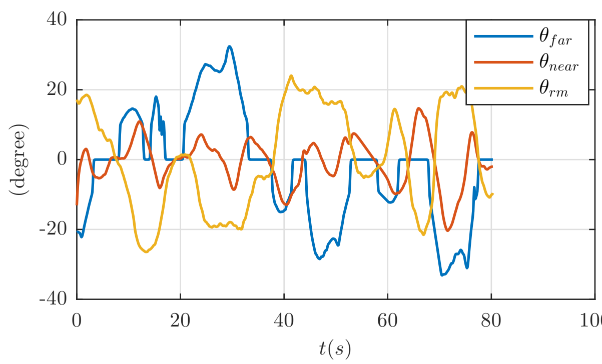

Fig. 7. Input signal (Validation data, Rider 1)

4.2 The motivations behind neural network identification

Once the input and output signals had been selected, it was necessary to specify the characteristics of the model.

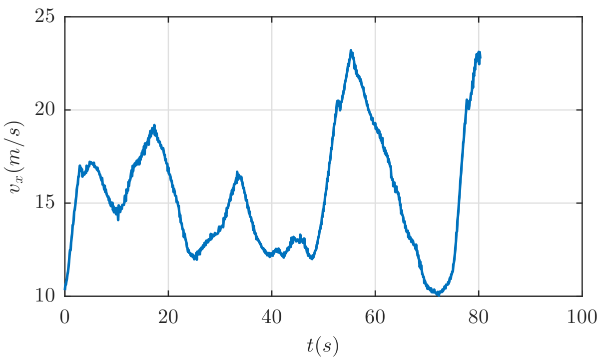

Fig. 8. Longitudinal speed (Validation data, Rider 1)

First, the multivariable coherence between all the input signals and each output signal was computed. This indicator highlighted that the relationship between the inputs (speed excluded) and the steering angle is mostly (but not entirely) linear. However, as discussed in Section 5.3, linear identification does not lead to satisfactory prediction capabilities. Consequently, the model chosen here for identification purposes is a possibly nonlinear dynamic neural network model. This type of black box model is far from the desired cybernetic model but is very interesting at this stage due to its investigation capabilities.

In addition, with the limited constraints imposed on the neural network model and its ability to approximate a large class of nonlinear models, it can be expected to achieve a very satisfying level of identification and prediction performances. If data are rich enough, the time delay neural network model will constitute a reference in terms of achievable performance in future attempts to create a cybernetic model.

4.3 Time delay neural network

In this paper, the considered neural network is a multi input multi output (MIMO) time delay neural network with a single hidden layer (as represented in Figure 9). The relation between the inputs and outputs of this network can be written as follows:

$$y_m(k) =$$
$$\sigma^0 \left(\sum_{i=1}^{N} w_{im}^0 \, \sigma^1 \left(\sum_{j=1}^{n_i} \sum_{l=1}^{n} w_{ijlm}^1 \, u_j(k-l) + b_{im}^1 \right) + b_m^0 \right).$$

In this expression, y_m is the network output signal number m, u_j is the network input signal number j, σ^0 and σ^1 are the activation functions (respectively linear $\sigma^0(x) = x$ and sigmoid $\sigma^1(x) = 2/((1+\exp(-2x))-1)$ in this paper), w_{im}^0 and b_m^0 are the weights and bias of the output layer, w_{ijlm}^1 and b_{im}^1 the weights and bias of the hidden layer, N is the number of neurons, n the number of input delays and finally n_i the number of input signals.

Such a model, with a single hidden layer, permits the approximation of a large class of nonlinear functions. The model can be restricted to a linear model by selecting linear activation functions σ^0 and σ^1. In this case, it reduces to a simple finite impulse response (FIR) filter. The finite number of input delays considered in the model

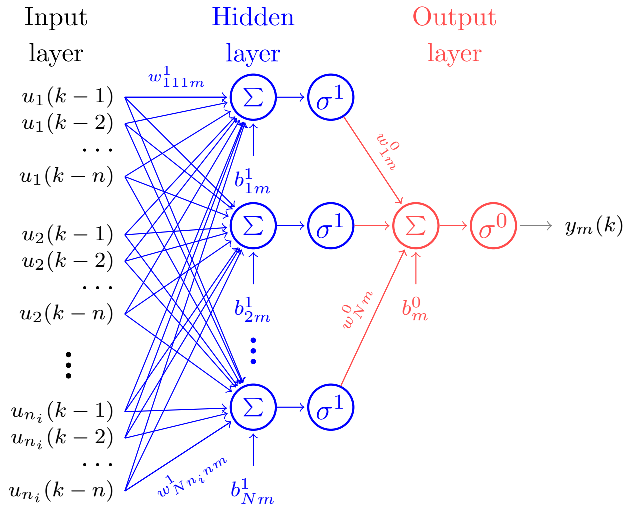

Fig. 9. MIMO TDNN with a single hidden layer

formalizes the fact that a motorcycle rider exploits only recent informations from their inputs to make decisions.

The neural network training presented in this paper was realized with Matlab's Neural Network Toolbox$^{\text{TM}}$.

5. ANALYSIS OF RESULTS

Three important questions are addressed in this section. The first is: which input signals should be chosen for the rider model to obtain good predictive capacities. Once a correct result is obtained for a given rider, the second question arises: is the model sufficiently rich to account for the behavior of a large variety of riders? Finally, the third question involves the nonlinearity of the model.

All these questions were analysed using the classical Fit indicator for evaluating model accuracy:

$$\text{Fit} = 100 \left(1 - \frac{\|y_e - y_m\|_2}{\|y_e - \bar{y}_e\|_2} \right).$$

In this expression, y_e and y_m denote respectively the experimental signal and the model output signal, while $\bar{y}_e$ is the average of signal y_e. If the Fit indicator is equal to 100, the model output y_m perfectly matches the experimental data. In general, a Fit value above 80 is considered good.

5.1 Input and output signals vs. prediction capabilities

A key issue with rider modeling is the selection of appropriate input signals, that contain enough information to predict the model output signals. This input selection has been evaluated using the Fit indicator presented above. In Table 1, "Fit (id)" designates the Fit value obtained with the identification data, while "Fit (va)" indicates the one obtained with the validation data. "Fit (id)" is of course always better than "Fit (va)" and the latter is the most meaningful indicator of model prediction performance.

Three input sets were tested. First, u_1 considers only the visual feedback. As one can see from the first line of Table 1, u_1 allows one to partially predict the steering angle δ, but the correspondence between the model output

Table 1. Fit indicator obtained with a nonlinear TDNN for rider 1 when changing the model inputs and outputs ($u_1 = [\theta_{far}, \theta_{near}]^T$, $u_2 = [\theta_{far}, \theta_{near}, v_x]^T$, $u_3 = [\theta_{far}, \theta_{near}, \theta_{rm}, v_x]^T$)

Input	Output	Fit (id)	Fit (va)	n	N
u_1	δ	94.7	67.0	20	20
u_2	δ	97.5	78.0	20	20
u_3	δ	98.8	84.5	25	20
u_3	$[\delta\ \theta_{rr}]^T$	98.2 99.0	84.1 85.6	30	20

and the measured (validation) data presented in Figure 10 is not fully satisfactory.

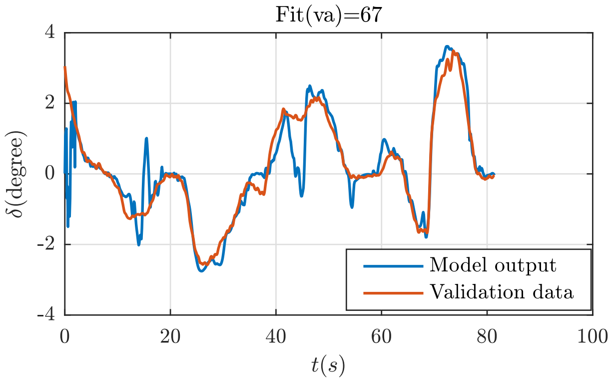

Fig. 10. Comparison of the TDNN model output δ with the validation data (Rider 1, Input u_1, Output δ)

Remark 1. The initial errors in Figures 10, 11 and 12 are due to the initialization of the network and are unavoidable and not significant. They are not considered in the calculation of the Fit indicator.

Adding the longitudinal speed as input (that is considering u_2) offers additional prediction capabilities (see the second line of Table 1). This crucial result was expected as it matches knowledge from car driver modeling. The nature of the speed influence is not yet explicit, but its importance is highlighted with a Fit (va) improved by more than 10%.

Finally, adding the motorcycle roll signal θ_{rm} as an input allows the model to reach very good prediction accuracy ("Fit (va)" above 80 on line 3 and 4 of table 1). This result is confirmed by Figures 11 and 12 which represent the match obtained for δ and θ_{rr}, respectively, with the validation data for the configuration of the last line of Table 1.

In short, the necessary input signals are : θ_{far}, θ_{near}, θ_{rm} and v_x. They allow the model to properly predict the steering angle δ and the rider roll angle θ_{rr}.

Remark 2. One may note that the value of n is not always the same in Table 1 (and also in Table 3). In each input and output configuration, several values were tested for n (and also N) with different initial conditions. The value retained is the one with the best prediction performance.

5.2 Generalization to different riders

Once the best input configuration was established for one rider (rider 1), it was tested with five others riders to validate the ability of the model to achieve satisfactory

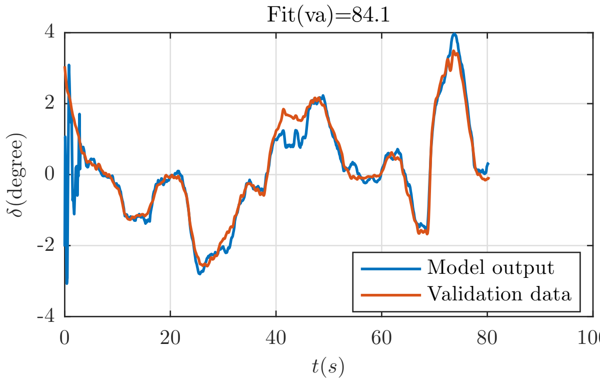

Fig. 11. Comparison of the TDNN model output δ with the validation data (Rider: 1, Input: u_3, Output: $[\delta\ \theta_{rr}]^T$)

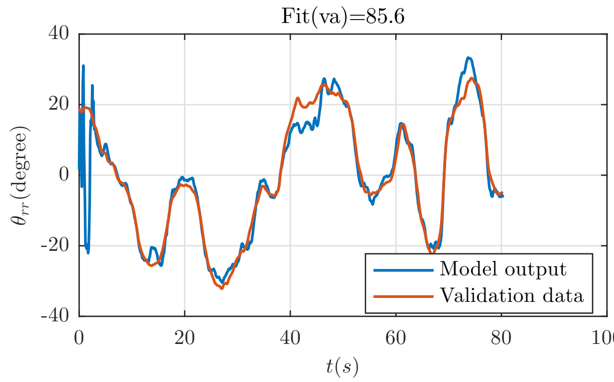

Fig. 12. Comparison of the TDNN model output θ_{rr} with the validation data (Rider: 1, Input: u_3, Output: $[\delta\ \theta_{rr}]^T$)

results for a variety of riders. As seen in Table 2, results obtained for riders 2 to 6 are very similar to those obtained with rider 1 (the reference rider).

Table 2. Fit indicator obtained with a nonlinear TDNN for different riders (Input: $[\theta_{far}, \theta_{near}, \theta_{rm}, v_x]^T$)

Rider	Output	Fit (id)	Fit (va)
1	δ	98.8	84.5
2	δ	98.4	88.0
3	δ	99.0	88.6
4	δ	98.9	81.4
5	δ	98.6	80.2
6	δ	98.5	86.3
1	$[\delta\ \theta_{rr}]^T$	98.2 99.0	84.1 85.6
2	$[\delta\ \theta_{rr}]^T$	98.0 98.9	89.0 88.8
3	$[\delta\ \theta_{rr}]^T$	98.2 99.2	89.0 88.5
4	$[\delta\ \theta_{rr}]^T$	97.3 98.3	84.0 84.1
5	$[\delta\ \theta_{rr}]^T$	98.1 98.4	82.1 80.0
6	$[\delta\ \theta_{rr}]^T$	97.0 98.4	85.8 90.8

5.3 Linear/nonlinear

The results presented in Table 3 are the same as those presented in the last two lines of Table 1, but the results in Table 3 were obtained with a linear time delay neural network ($\sigma^0(x) = \sigma^1(x) = x$). The degradation of the prediction performance for δ when imposing model linearity is apparent. Furthermore, the neural network's use of speed is not clear in this case. However, the loss of performance is not that significant. It can even be said that, although the motorcycle is a nonlinear system, the rider's behavior is predominantly linear.

Table 3. Fit indicator obtained with a *linear* TDNN for rider 1 (Input: $[\theta_{far}, \theta_{near}, \theta_{rm}, v_x]^T$)

Output	Fit (id)		Fit (va)		n	N
δ	76.0		72.0		20	20
$[\delta\ \theta_{rr}]^T$	74.4	85.9	74.7	85.2	10	20

6. CONCLUSION

This paper discusses the identification of a motorcycle rider model based on experimental data recorded during road tests with a fully instrumented motorcycle. The main contribution of this work is the proposal of a black box rider model in the form of a time delay neural network. This model has enabled the investigation of several important questions. It was first confirmed that the considered experimental data are sufficiently rich to identify a rider model. Strong prediction capabilities were obtained for various riders. In addition to the longitudinal speed, θ_{near} and θ_{far} (for visual perception), and θ_{rm} (for vestibular perception), have been validated as a set of explicative inputs that are well suited to predict rider actions in terms of steering angle and even rider roll angle θ_{rr}. Finally, despite the nonlinearity of the motorcycle-road system, rider behavior seems to be predominantly linear. These very encouraging results allow to target a more gray box rider model and to gradually progress toward a cybernetic rider model.

REFERENCES

Bocciolone, M., Cheli, F., Leo, E., and Pezzola, M. (2007). Experimental identification of kinematic coupled effects between driver – motorcycle. In *IMAC - XXV: a conference & and exposition on structural dynamics*, 19,22. Orlando,FL.

Donges, D.E. (1978). A two-level model of driver steering behavior. *Human Factors*, 20(6), 691–707.

Espié, S., Larnaudie, B., Vincke, B., Delgehier, F., Sadoun, R., Bouaziz, S., Mammar, S., Mars, F., Laubenheimer, C., and Reynaud, J.P. (2016). In-depth study of bend taking practices, towards evaluation and (re)training tools : the VIROLO++ research project. In *11th International Motorcycle Conference*. Cologne, Germany.

Evertse, M. (2010). *Rider analysis using a fully instrumented motorcycle*. Master's thesis, Delft University of Technology.

Frissen, I. and Mars, F. (2014). The effect of visual degradation on anticipatory and compensatory steering control. *Quarterly Journal of Experimental Psychology*, 67(3), 499–507.

Hosman, R. (2009). The use of pilot models to support flight simulation: The sky is the envelope. In *Royal Aeronautical Society Conference*. London.

Katayama, T., Aoki, A., and Nishimi, T. (1988). Control behaviour of motorcycle riders. *Vehicle System Dynamics*, 17(4), 211–229.

Kooijman, J. and Schwab, A. (2013). A review on bicycle and motorcycle rider control with a perspective on handling qualities. *Vehicle System Dynamics*, 51(11), 1722–1764.

Land, M. and Horwood, J. (1995). Which parts of the road guide steering? *Nature*, 377, 339–40.

Lone, M. and Cooke, A. (2014). Review of pilot models used in aircraft flight dynamics. *Aerospace Science and Technology*, 34, 55 – 74.

Mammar, S., Espie, S., Glaser, S., and Larnaudie, B. (2006). Experimental Validation of Static H_∞ Rider for Motorcycle Model Roll Stabilization. In *2006 IEEE Intelligent Vehicles Symposium*, 498–503.

Popov, A.A., Rowell, S., and Meijaard, J.P. (2010). A review on motorcycle and rider modelling for steering control. *Vehicle System Dynamics*, 48(6), 775–792.

Prem, H. and Good, M.C. (1983). A rider-lean steering mechanism for motorcycle control. In *8th IAVSD Symposium on the Dynamics of Vehicles on Roads and on Tracks*, 422–435. Massachusetts Institute of Technology, USA.

Prem, H. and Good, M.C. (1984). Motorcycle rider skills assessment. Technical report, University of Melbourn, Parkville, Victoria.

Rice, R.S. (1978). Rider skill influences on motorcycle maneuvering. In *SAE Technical Paper*. SAE International.

Saleh, L., Chevrel, P., Claveau, F., Lafay, J., and Mars, F. (2013). Shared steering control between a driver and an automation: Stability in the presence of driver behavior uncertainty. *IEEE Transactions on Intelligent Transportation Systems*, 14(2), 974–983.

Salvucci, D. and Gray, R. (2004). A two-point visual control model of steering. *Perception*, 33(10), 1233–1248.

Sharp, R.S. (2006). Optimal linear time-invariant preview steering control for motorcycles. *Vehicle System Dynamics*, 44(sup1), 329–340.

Sharp, R.S. (2007). Motorcycle steering control by road preview. *Journal of Dynamic Systems Measurement and Control-transactions of The Asme - J DYN SYST MEAS CONTR*, 129.

Weir, D.H. (1973). A manual control view of motorcycle handling. In *Proceedings of the Congress on Automotive Safety*. San Francisco.

Weir, D.H. (1972). *Motorcycle handling dynamics and rider control and the effect of design configuration on response and performance*. Ph.D. thesis, University of California, Los Angeles, USA.

Zellner, J.W. and Weir, D.H. (1978). Development of handling test procedures for motorcycles. In *SAE Technical Paper*. SAE International.