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Rider model identification: neural networks and quasi-LPV models

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Abstract: The current development of Advanced Rider Assistance Systems (ARAS) would interestingly benefit from precise human rider modelling. Unfortunately, important questions related to motorbike rider modelling remain unanswered. The goal of this study is to propose an original cybernetic rider model suitable for ARAS oriented applications. The identification process is based on experimental data recorded in real driving conditions with an instrumented motorbike. Starting with a dynamic neural network, the proposed methodology firstly presents a non-linear rider model. The analysis of this model and some analogies with car driver modelling allow to deduce a quasi-linear parameter varying (quasi-LPV) rider model with explicit speed dependence and a clear distinction between linear and non-linear dynamics. This quasi-LPV model is further analysed and simplified and finally leads to a rider model with a reduced number of parameters and nice prediction capabilities. Such a model opens up interesting perspectives for the improvement of rider assistances.

1 Introduction

The goal of the current development of Advanced Rider Assistance Systems (ARAS) is to improve the safety of motorbike drivers, who remain year after year one of the most vulnerable road users. For instance, in France in 2018 the ONISR (French observatory of road safety) related that the risk of being killed was 22 times higher for a motorbike rider than for a car driver, making motorbikes an ongoing central issue of road safety.

Enhanced safety on motorcycles began with the airbag, anti-lock braking system and electronic stability control. These features are now available at least on high-end motorcycles. However, a motorcycle is harder to control than a car. Assisting the rider in performing that task, therefore, remains a major road safety issue. This is the main motivation for the current research on ARAS.

Any ARAS is developed to help the rider in his driving task and should preferably take the rider's behaviour into account. As for cars, where driver modelling is used in the design of many assistance systems, motorbike rider modelling is expected to be a key element to improve the system efficiency, but also the acceptability by the riders of various ARAS. In this context, the objective of this paper is to provide a simple cybernetic rider model allowing to predict accurately the steering angle, which is used for instance in departure lane assistance (DLA) systems. Such a model would help to improve the realism of indicators such as time or distance to lane crossing (TLC or DLC). It could be involved in a similar application as the one presented in [1] which uses a driver model to evaluate the lane departure risk in the car driving context.

The presented approach for rider modelling is based on experimental data recorded in real driving conditions with an instrumented motorbike. Thus, the main contribution of the paper is to propose an investigation methodology from experimental data to a simple rider model ready to use in the ARAS context.

The content of the paper is organised as follows. Section 2 summarises the literature and the cybernetics assumptions made in the proposed approach. Section 3 presents the experimental data supporting the identification process and the instrumented motorbike used to record these data. Sections 4, 5 and 6 discuss the proposed methodology. First, Section 4 presents the weaknesses of a linear identification approach and motivates the use of a dynamic neural network. Section 5 analyses the performance and the non-linearity of a dynamic neural network rider model. Based on this analysis, Section 6 derives a quasi-linear parameter varying (quasi-LPV) model whose analysis and simplification lead to a simple cybernetic rider model suitable for ARAS applications. Finally, the conclusion summarises the contributions of the paper, the strengths of the proposed model and the main perspectives of this work.

2 Rider modelling

Before the experiment and the modelling problem are presented, this section summarises the existing literature on motorbike rider modelling and presents the main assumptions of the paper.

2.1 State-of-the-art

A motorbike is an unstable system (at least statically) with significant roll dynamics. The difference between the mass of the vehicle and that of the rider is considerably smaller for motorbikes than for cars. This makes motorbike driving more complex than car driving. As a consequence, rider modelling is difficult and remains a significant research challenge.

A significant portion of the literature on rider modelling 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 motorbike riding deals either with rider observation or rider modelling. A general overview of this work is given in [2, 3]. In the domain of rider observation, the main addressed topics are handlebars control (steering torque versus steering angle), the prevalence of different forms of control (handlebars versus rider lean) [4–6] and the differences between experienced and novice riders [5, 7, 8]. The conclusions vary depending on the considered manoeuvre, but in general, novice rider behaviour 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 motorbike. This importance may vary according to the speed. Finally, most papers conclude that a human rider controls a motorbike by applying a steering torque rather than a steering angle. More

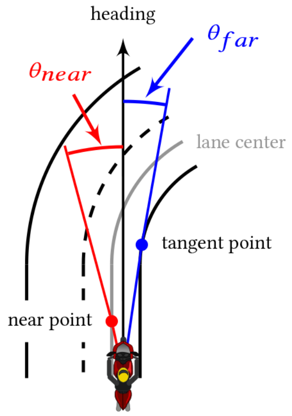

Fig. 1 *Angles θ_{near} and θ_{far}*

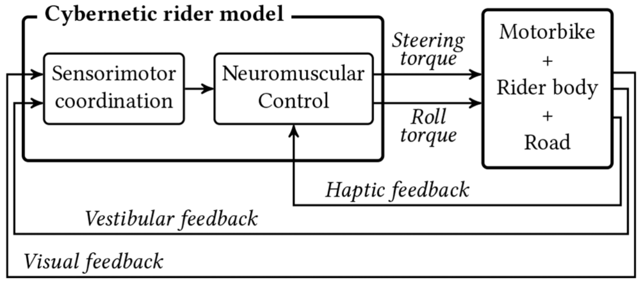

Fig. 2 *Cybernetic rider model*

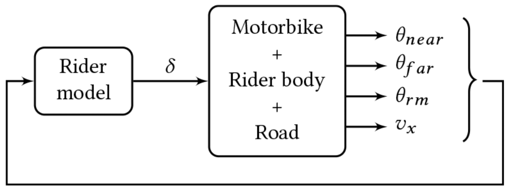

Fig. 3 *Simplified cybernetic rider model*

recently, Frank *et al*. [9] used an instrumented motorbike to record and analyse the rider control inputs during typical manoeuvres.

The literature on rider modelling can be divided into two groups: human rider modelling and automatic control. The papers on human rider modelling [10–12] are mainly based on a theoretical approach and are not necessarily validated with experimental data. The proposed models in [10, 11] 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 formalised. Prem and Good [12] have used a similar model adapted to novice riders. The automatic control-based literature [13–18] replaces the human rider with a controller. The conclusions in [15] indicate that the handlebar steering torque is the main method used to control a motorcycle. Edelmann *et al*. [19] draw the same conclusion for the bicycle case. Sharp [13, 14] has analysed 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. More recently, Mouad and Saka [17] analyse the performances of an automatic rider in the form of a PID controller and Nishimura *et al*. [18] proposed a rider model for the racing simulation that incorporates non-linear model predictive control.

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

Car driver modelling 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 [20–22]. To formalise this dual process, two indicators are generally used to reproduce human visual perception. In [1, 23], these two indicators take the form of two angles named θ_{near} and θ_{far} (they are illustrated in Fig. 1). 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 formalised in the cybernetic model proposed by Saleh *et al*. [1].

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 [24, 25]. Motorcycle modelling shares elements of both car driver modelling (both have similar visual control of trajectory) and aircraft pilot modelling. The dynamics of movement are more constrained in a motorcycle than in aeroplanes, 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 behaviour 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 Fig. 2. The model incorporates three types of feedback used by a human rider to control a motorbike: 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 not the goal of this paper. The proposed model is inspired by this cybernetic approach but focuses on a different objective, that is to derive a simple rider model suitable for supporting the development of ARAS such as for instance DLA systems. This type of system is based on the detection/prediction of lane crossing through risk functions involving indicators such as TLC and DLC. Currently, these indicators are only based on the prediction of the motorcycle trajectory without any prediction of the rider control. Combining in an observer the prediction of the motorcycle behaviour and of the rider steering angle would necessarily improve the realism and the reliability of such indicators.

Thus, the model considered in this paper (see Fig. 3) is a simplified version of the model of Fig. 2. The main simplification concerns the output of the rider model. A human rider controls his motorbike through a steering torque applied to the handlebars which is adjusted using a haptic feedback. The application of the paper is more interested in the steering angle estimation rather than the steering torque, the considered model output is the steering angle and consequently, no haptic feedback is considered. The roll torque introduced with the rider upper body, which is generally considered as secondary with regard to the action on the handlebar is also neglected here.

The hypothesis of this study concerning visual feedback is that the analysis of the visual scene conducted by a motorbike 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} [1]. As illustrated in Fig. 1, 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 centre of the lane, 5 m ahead of the vehicle. The tangent point is used to anticipate the upcoming road curvature. Such indicators are not

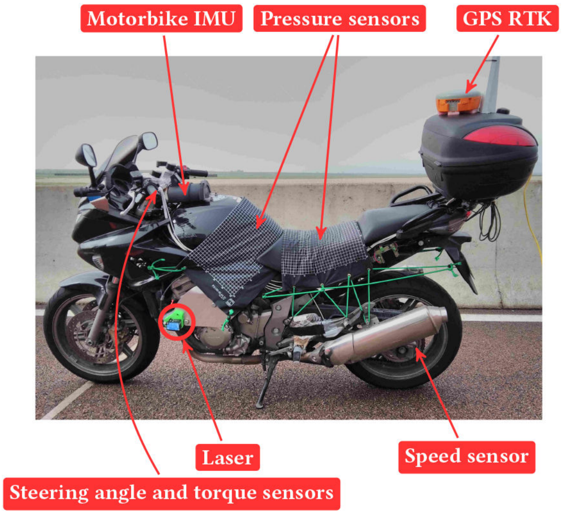

Fig. 4 *Instrumented motorbike (VIROLO++ project)*

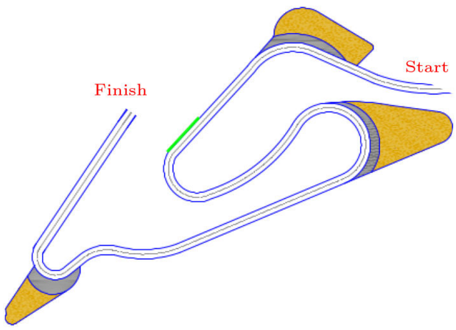

Fig. 5 *Track used for the experiment*

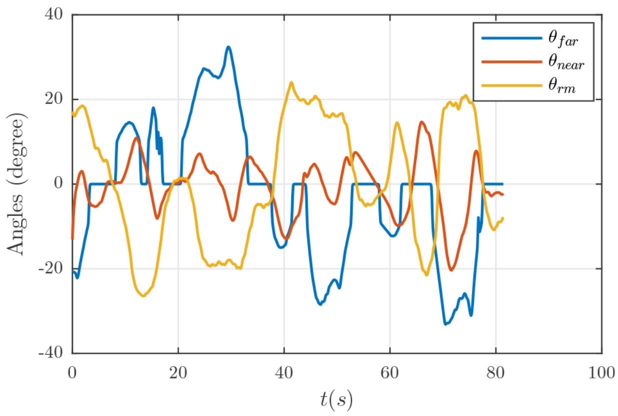

Fig. 6 *Input signal (Validation data)*

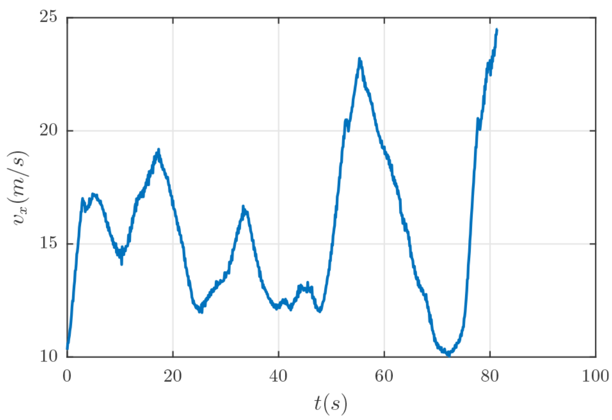

Fig. 7 *Longitudinal speed (Validation data)*

directly measured on the instrumented motorbike 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 motorbike roll motion, which is taken into account in this paper by considering $\theta_{\rm rm}$ (the roll angle of the motorbike) as an input of the rider model.

The rider model used in this work is summarised in Fig. 3. The inputs are the near angle $\theta_{\rm near}$, the far angle $\theta_{\rm far}$ and the roll of the motorbike $\theta_{\rm rm}$. The output considered is the steering angle δ. The longitudinal speed v_x constitutes an additional model input, as it certainly affects the rider model dynamics.

Based on these assumptions and the experimental data presented in Section 3, the proposed identification approach is presented in Section 4.

3 Experiment

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

3.1 Instrumented motorbike

The instrumented motorbike, a Honda CBF 1000, is presented in Fig. 4. The instrumentation was designed for various applications (trajectory reconstruction, motorbike model identification, rider model identification etc.) [26]. It is mainly composed of: quadratic encoders (on the front and rear wheels), two motorbike inertial measurement units (IMUs), two laser sensors on the left and on the right of the motorbike (for measuring the left and right distance to the floor and reconstructing the motorbike roll angle), a steering angle sensor, strain gauges on the handlebars and on the footrests, pressure sensors on the seat and on the tank of the motorbike, a standard GPS, a real time kinematic (RTK) GPS and IMUs placed on the rider back and head.

As this paper uses only a restricted set of the available sensors, the instrumentation is only partly described in Fig. 4. The considered sensors for the presented application are the RTK GPS for the trajectory recording, the motorbike IMU for measuring the roll angle, the steering angle sensor and the speed sensor of the rear wheel. All the signals used were synchronised while recording and sampled at 0.1 s.

3.2 Road tests and experimental data

The road tests were conducted on a track (presented on Fig. 5), in dry conditions, with novice riders of the French military force. After a driving time given to discover and getting used to the motorbike, each rider was asked to realise three laps without driving instruction (normal driving) and several laps with specific driving instructions. These road tests were also completed with subjective evaluations before and after the driving session.

This paper considers the identification of a rider model in normal driving conditions. Thus, the identification is based on two laps of normal driving, one for the identification itself and a second for the validation of the model. Only one of the riders is considered. The selected rider for the paper is the median rider in terms of prediction performance. Similar results were obtained with other riders that validate the approach. The subjective evaluations and the analysis of the specific driving instructions are out of the scope of this paper. Examples of model input signals obtained from experimental data are shown in Figs. 6 and 7. While experimental records of the model output signal δ are given in Section 5.2. Most of these signal required pretreatments (filtering, reconstruction from sensors signal). These pretreatments are not presented here for readability.

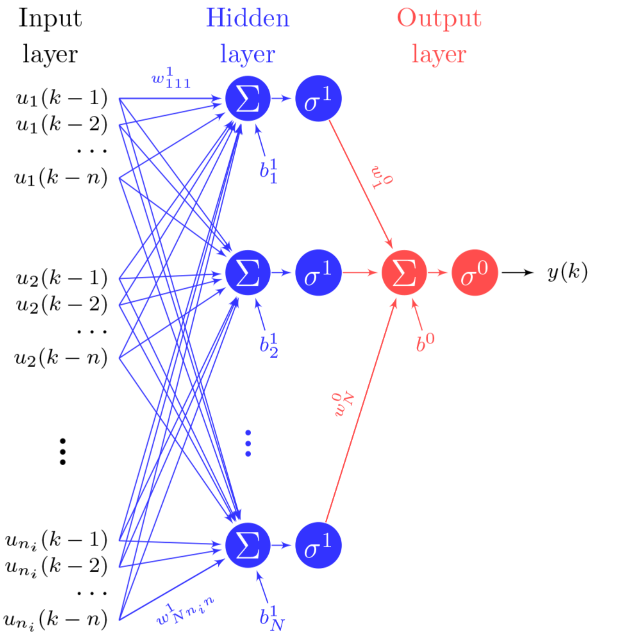

Fig. 8 *MISO TDNN with a single hidden layer*

Table 1 Fit indicator obtained with a TDNN

TDNN	Fit (id)	Fit (va)	n	N
non-linear	98.8	84.5	25	20
linear	76.0	72.0	20	20

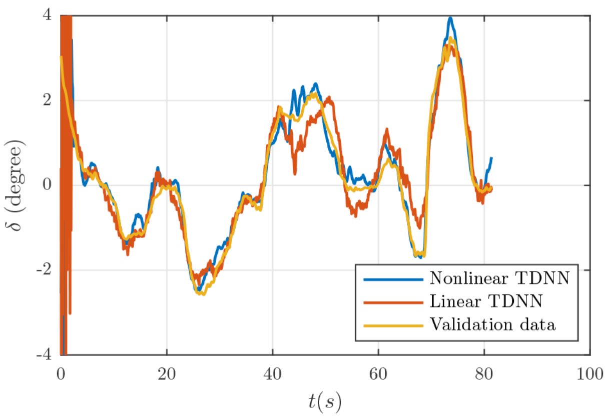

Fig. 9 *Comparison of the TDNN models output δ with the validation data*

4 Linear identification

Based on the assumptions made in Section 2.2 and the selection of inputs and output for the rider model, this section presents the identification problem.

First, the multivariable coherence [27] between all the input signals and the output signal was computed. This frequency indicator allows to analyse if there exists a linear and stationary relation between the inputs and the considered output signals. It highlighted that the relation between the inputs (speed excluded) and the steering angle is mostly (but not entirely) linear. At the same time, linear identification does not lead to satisfactory prediction capabilities.

The indicator used for evaluating the model accuracy is the classical Fit indicator:

$$\text{Fit} = 100\left(1 - \frac{\| y_\text{e} - y_\text{m} \|_2}{\| y_\text{e} - \bar{y}_\text{e} \|_2}\right).$$

In this expression y_e and y_m denote the experimental signal and the model output signal, respectively, while $\bar{y}_\text{e}$ is the average of the 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 as good.

The linear and stationary models obtained from linear identification failed to reach such a level of model accuracy.

The next step in the proposed approach is then to consider a non-linear model in the form of a time delay neural network (TDNN). This is presented in Section 5. Based on the analysis of this non-linear rider model a quasi-LPV model could be derived and is presented in Section 6.

5 Neural network identification

Selecting a dynamic neural network model allows to consider non-linear dynamics and to reproduce more accurately the rider behaviour. Among the different types of dynamic neural network, the TDNN was selected for its simplicity and its ability to approximate a large class of non-linear models.

5.1 Time delay neural network

In this paper, the considered neural network is a multi-input single-output (MISO) TDNN with a single hidden layer (as represented in Fig. 8). The relation between the inputs and outputs of this network can be written as follows:

$$y(k) = \sigma^0\left(\sum_{i=1}^{N} w_i^0\, \sigma^1\left(\sum_{j=1}^{n_i}\sum_{l=1}^{n} w_{ijl}^1\, u_j(k-l) + b_i^1\right) + b^0\right).$$

In this expression, y is the network output signal, 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_i^0 and b^0 are the weights and bias of the output layer, w_{ijl}^1 and b_i^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, does not have the property of universal approximation (for single-layer networks it requires a special type of neuron [28]) but permits the approximation of a large class of non-linear 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 linear finite impulse response filter. The finite number of input delays considered in the model formalises the fact that a motorbike rider exploits only recent information from their inputs to make decisions.

The neural network training presented in this paper was realised with Matlab Neural Network Toolbox™.

5.2 Analysis of the TDNN model

In this section, the prediction of the TDNN model is analysed and the necessity of the non-linear behaviour is questioned.

5.2.1 Prediction performance: The model accuracy is evaluated through the above presented Fit indicator. 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.

Remark 1: In the linear and non-linear configurations several values were tested for n and N with different initial conditions. The values retained in each configuration are the ones with the best prediction performance.

The selection of inputs and the choice of a TDNN model allow to reach very good prediction capabilities of the steering angle δ ('Fit (va)' being above 80 in the first line of Table 1). This result is confirmed by Fig. 9 (blue line). The difference between Fit (id) and Fit (va) in the non-linear case indicates that the TDNN model is a bit over-parametrised and could probably be reduced. This refinement was not further analysed here as the objective was primary to demonstrate the prediction capabilities.

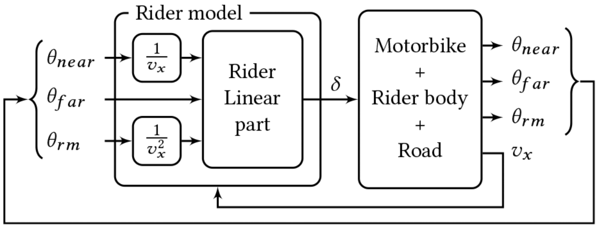

Fig. 10 *Quasi-LPV rider model*

Table 2 Fit indicator obtained with a quasi-LPV model

Quasi-LPV model	Fit (id)	Fit (va)	Order
full	85.7	81.8	3
simplified	80.5	76.9	3

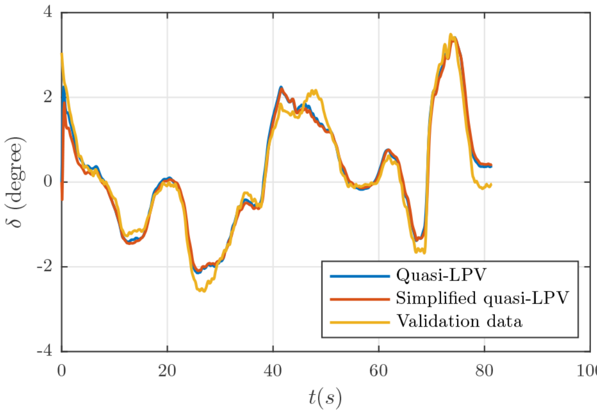

Fig. 11 *Comparison of the quasi-LPV models output δ with the validation data*

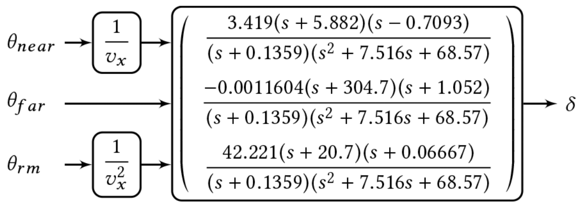

Fig. 12 *Quasi-LPV rider model (zpk transfers)*

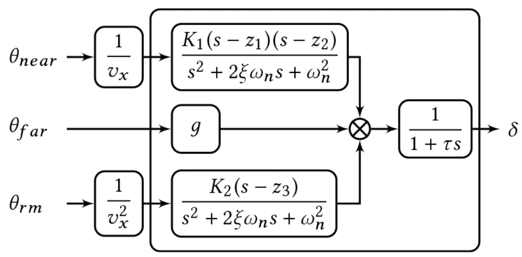

Fig. 13 *Quasi-LPV rider model after simplification*

Remark 2: The initial errors in Fig. 9 are due to the initialisation of the network and are unavoidable and not significant. They are not considered in the calculation of the Fit indicator.

Tests conducted with five other riders confirm the prediction capabilities of the non-linear TDNN model. For these other pilots, Fit (va) ranges from 80.2 to 88.6.

5.2.2 Linear/non-linear: The result presented in the second line of Table 1 is the same as the one presented in the first line, but the result in the second line was obtained with a linear TDNN ($\sigma^0(x) = \sigma^1(x) = x$). The degradation of the prediction performance for δ when imposing the 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 motorbike is a non-linear system, the rider's behaviour is predominantly linear.

This result is confirmed in Fig. 9 (red line).

6 Quasi-LPV identification

The conclusions of the TDNN identification confirm that it is possible to identify a non-linear rider model with relevant prediction capabilities. The use of a linear TDNN model indicates that the rider model is not strongly non-linear. This result was already deduced from the analysis of the multivariable coherence discussed in Section 4. It would then be very helpful to separate the non-linear and linear parts of the model. The non-linear behaviour is suspected to be closely related to the speed influence on the rider behaviour. In the car driver model presented in [1], the speed divides the input signal θ_{near}. As it is assumed in this paper that the visual feedback is similar in cars and on a motorbike, the same assumption with regard to the speed is considered. On the other side it is well-known that a motorbike roll motion is influenced by the square of the longitudinal speed. Then the second assumption made in this section is to normalise the motorbike roll signal θ_{rm} by the square of the speed. The rest of the rider model is considered to be linear. The resulting quasi-LPV model is presented in Fig. 10.

6.1 Model identification

The identification of the linear part of the quasi-LPV model was conducted with the subspace-based algorithm N4SID. It leads to very good model accuracy (see the first line of Table 2 and Fig. 11 (blue line)). The Fit value obtained is a bit lower than with the TDNN model, but the number of parameters involved in this model is drastically smaller. Its structure, at least the speed influence, is also much more readable.

6.2 Model analysis and simplification

The details of the model parameters are provided in Fig. 12 in the form of zeros/poles/gain (zpk) transfers.

The transfer between θ_{near} and δ contains a non-minimum phase zero. It is probably linked to the use of counter-steering and the related non-minimum phase behaviour of the motorbike. The fact that it affects only the transfer between θ_{near} and δ indicates that the counter-steering is used for rapid compensation rather than for anticipating the coming trajectory using θ_{far}. It may also explain that the counter-steering is sometimes very small when a bend is well anticipated with θ_{far}.

The three poles (one real and two complex conjugates) are common to the three transfers, but the two complex conjugates poles appear to affect essentially the transfer between θ_{rm} and δ (Cf. the bode diagram not provided here and gramians). It appears that they can be simplified in the transfer between θ_{far} and δ. The time constant related to the real pole is close to 7.3 s.

The high-frequency zeros of the transfers between θ_{far}, θ_{rm} and δ can also be removed. These simplifications lead to the rider model presented in Fig. 13, whose parameters K_1, K_2, g, z_1, z_2, z_3, ξ, ω_n and τ are deduced directly from the values given in Fig. 12 without further optimisation.

The accuracy of this simplified model remains acceptable as one can see from the second line of Table 2 and Fig. 11 (red line).

7 Conclusion

While it could constitute an interesting source of improvement for ARAS technologies, the literature dealing with cybernetic rider modelling remains rather poor with very rare experimental validations. In this context, the contribution of this paper is to propose an original rider model obtained from closed-loop experimental data that is compatible with ARAS applications needs.

The proposed investigation methodology from the experimental data to the selected rider model proceeds in several steps. First, as a linear time-invariant model was not able to capture all the rider dynamics, a fully non-linear model (in the form of a TDNN) was considered. It offers a very good prediction level, but involves a significant number of parameters and is not suitable for analysing and understanding precisely the rider behaviour. In addition, this work has shown that the rider model is not strongly non-linear. It can be written in the form of a quasi-LPV model composed of two parts: a linear time-invariant one and a second parametrised by the longitudinal speed. With this structure, the model retains a very good prediction ability and offers a better understanding of the rider behaviour such as the use of counter-steering. Finally, some of the dynamics of this quasi-LPV model could be simplified without too much loss of prediction performance. The resulting cybernetic model has a very reduced number of parameters and is relevant for use in the ARAS context where it could help to improve the realism of indicators such as TLC and DLC that are used in LDA systems.

One rider was selected for the paper, but prediction results obtained with other riders are very similar. The quasi-LPV models obtained with the other riders involve different parameter values. Analysing the parameter variance to highlight invariants or disparities between riders is one of the perspectives of this paper.

8 Acknowledgments

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