

Multi-actuated ground vehicle tyre force estimation through a coupled 1D simulation-estimation framework

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Abstract—This paper disseminates the use of a coupled 1D simulation-estimation framework employed for multi-actuated ground vehicle tyre force virtual sensing. The forces generated in the tyre contact patches govern the vehicle motion and behaviour on the road. Therefore, they are highly relevant for Advanced Driver Assistance Systems (ADAS) and Automated Driving (AD) technologies, especially when it comes to ensuring vehicle stability and driving safety in extreme manoeuvres. However, some ADAS and AD features require accurate and robust estimation of additional vehicle dynamics related quantities. Thus, this paper proposes a framework for the consistent use of 1D vehicle models of different complexity together with state-of-the-art estimation techniques to enable joint state, disturbance, parameter (SDP) estimation.

Index Terms—state estimation, parameter estimation, simulation-estimation framework, tyre forces, Extended Kalman Filter

I. INTRODUCTION

Being the only connection from the vehicle to the road, tyres are of utmost importance for longitudinal and lateral vehicle dynamics and control.

Tyres are highly relevant for Advanced Driver Assistance Systems (ADAS) and Automated Driving (AD) as the tyre forces determine the way the vehicle behaves on the road. Thus, they are crucial for ensuring driving safety. However, the tyre forces and characteristics can only be measured directly

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with intrusive and/or expensive sensor equipment. Therefore, model-based virtual sensing, based on the standard set of sensors already implemented in current production vehicles, is a viable solution. That is, there is no extra cost implied, which is very important in the highly cost-sensitive automotive industry.

Furthermore, OEMs and tyre manufacturers are investigating automated objective tyre testing, see [1], for example for vehicle dynamics development purposes, in an effort to reduce development cost. Tyre force virtual sensing is enabling the use of this technology.

Typically, tyre force virtual sensors employ lumped parameter (1D) models to limit the computational cost, as well as to overcome observability limitations in distributed parameter models. Although model-order reduction techniques can be employed, these problems are often experienced when more complex 3D models containing exact geometric information are to be used. Furthermore, detailed 3D models are typically not available at the start of a development cycle but only in later stages. [2]

These lumped parameter models exist in different levels of complexity. To enable the consistent use of those different models, a framework to scale them is required. Therefore, an in-house developed estimation toolbox interfacing with the general purpose simulation software Siemens Simcenter Amesim [3] is employed in this work.

In this paper, longitudinal individual tyre forces F_x are estimated in open loop based on a rotating wheel dynamics model and signals of the electric motor torques as well as the brake pressures. For lateral tyre force F_y estimation, a tyre cornering stiffness estimation approach as proposed by [4]–[6] is followed.

The remainder of this paper is structured as follows: Section II introduces the estimation framework employing MATLAB, Simcenter Amesim, and the interface in between. The employed vehicle estimation model is described in Section III. This is followed by the validation of the estimation framework based on experimental test data in Section IV. Finally, Section V delivers the conclusion of this paper.

II. ESTIMATION FRAMEWORK

The estimation framework employed in this work is realised using MATLAB and Simcenter Amesim together with an in-house developed interface programmed in C as depicted by Fig. 1 [7]. The 1D vehicle model is implemented in Simcenter Amesim and the basis for the estimation exercise. The bond graph representation which is exploited in Simcenter Amesim inherently leads to a set of ordinary differential equations (ODEs) which are perfectly suitable for interaction with common estimation frameworks like the Kalman filter. The model communicates to MATLAB through a C interface in a bidirectional fashion, that is, the inputs and model parameters are fed to Simcenter Amesim from MATLAB and the model dynamics are used for the time update step of the estimator in MATLAB.

In this work we employ a general purpose estimation library in Matlab which supports a range of common estimators. Here we exploit the Extended Kalman Filter (EKF) implementation [8]. Through the C interface, the estimation library allows simultaneous estimation of states, disturbances, and parameters; so-called (joint) SDP estimation. For the underlying virtual sensing case of this paper, states (for the vehicle) and parameters (for the tyres) have been estimated jointly. In order to obtain the discrete model gradients required for the EKF, a central finite differencing approach is followed through the C interface.

It is important to remark that the interface directly links to the .dll file of the Simcenter Amesim vehicle model. Data is transferred through memory which results in a drastic speed-up ($>10^3$) compared to the standard file-based interaction with MATLAB, where data is constantly written to and read from .txt files.

III. VEHICLE ESTIMATION MODEL

The vehicle model used in the estimation framework is implemented in Simcenter Amesim and shown in Fig. 2. The central part of this vehicle model is the linear single track or “bicycle” model as introduced by [9], [10]. It is a chassis model with two degrees-of-freedom (DOF): the yaw rate $\dot{\psi}$ and the sideslip angle β of the vehicle body. Model inputs are the steering angle of the front wheel δ and the absolute vehicle velocity v_{abs} . Tyre behaviour is assumed linear, that is, the cornering stiffnesses are constant.

Two alterations are made to this classical model: (i) modeling the tyre slip angles α based on the planar vehicle body velocities v_x, v_y , the steering angle δ , and the yaw rate $\dot{\psi}$; (2) modeling of the wheel speeds v_{ij} based on $v_x, v_y, \delta, \dot{\psi}$. These choices add four DOF to the vehicle estimation model. Note

that small angles are assumed, allowing first order linearisation of trigonometric functions.

The Simcenter Amesim model implementation leads to the following state vector \mathbf{x} :

$$\mathbf{x} = \begin{bmatrix} \dot{\psi} \\ \psi \\ \beta \\ x_{COG} \\ y_{COG} \end{bmatrix} \quad (1)$$

where x/y_{COG} denote the COG position in the x and y directions of the global coordinate system. The measurement vector \mathbf{y} is defined as:

$$\mathbf{y} = \begin{bmatrix} \delta \\ v_{abs} \\ v_{fl} \\ v_{fr} \\ v_{rl} \\ v_{rr} \end{bmatrix} \quad (2)$$

The front and rear tyre cornering stiffnesses are modeled as unknown parameters and are estimated in a zero order hold with random walk approach [4], [5]. The per-axle lateral forces can be inferred from the front/rear cornering stiffnesses C_i and tyre slip angles α_i .

Longitudinal individual tyre forces F_x are estimated in open loop based on a rotating wheel dynamics model and signals of the electric motor torques as well as the brake pressures. For the sake of readability, this part of the Simcenter Amesim model is not included in Fig. 2.

v_x, v_y are numerically integrated in MATLAB from IMU measured vehicle body accelerations. Those have been corrected for influences of vehicle body pitch and roll angles following the approach proposed in [11].

All vehicle parameters are centrally defined in MATLAB and transferred to Simcenter Amesim via the C interface before the simulation run.

IV. VALIDATION

A. Experimental test vehicle

For the validation of the estimation framework, experimental test data was obtained using Flanders Make’s full electric Range Rover Evoque test vehicle [12] (in preparation), see Fig. 3. The vehicle specifications are shown in Table I.

Two independent electric motors are installed at the rear axle which provide equal torque for the given tests. The estimator input and measurement signals have been retrieved via the vehicle’s CAN bus: steering wheel angle (with known mapping to angle of left and right front wheels), wheel speeds, and brake pressures. The electric motors’ torque signals were acquired from the motor controllers. The data rate of all sensor signals had been limited to 100 Hz as this is the lowest physical data rate amongst the installed sensors. In order to obtain the reference signals, the following sensors have been added to the vehicle: an inertial measurement unit (IMU) to capture the translational accelerations and angular velocities of the

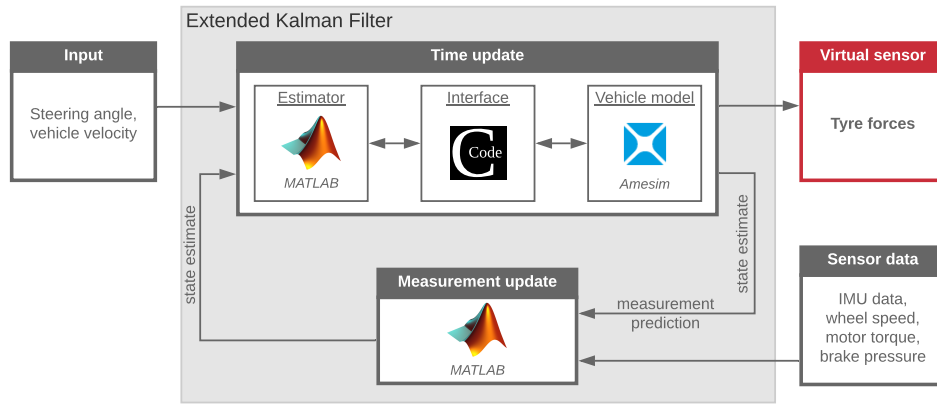


Fig. 1. Estimation framework (based on [2], [7]).

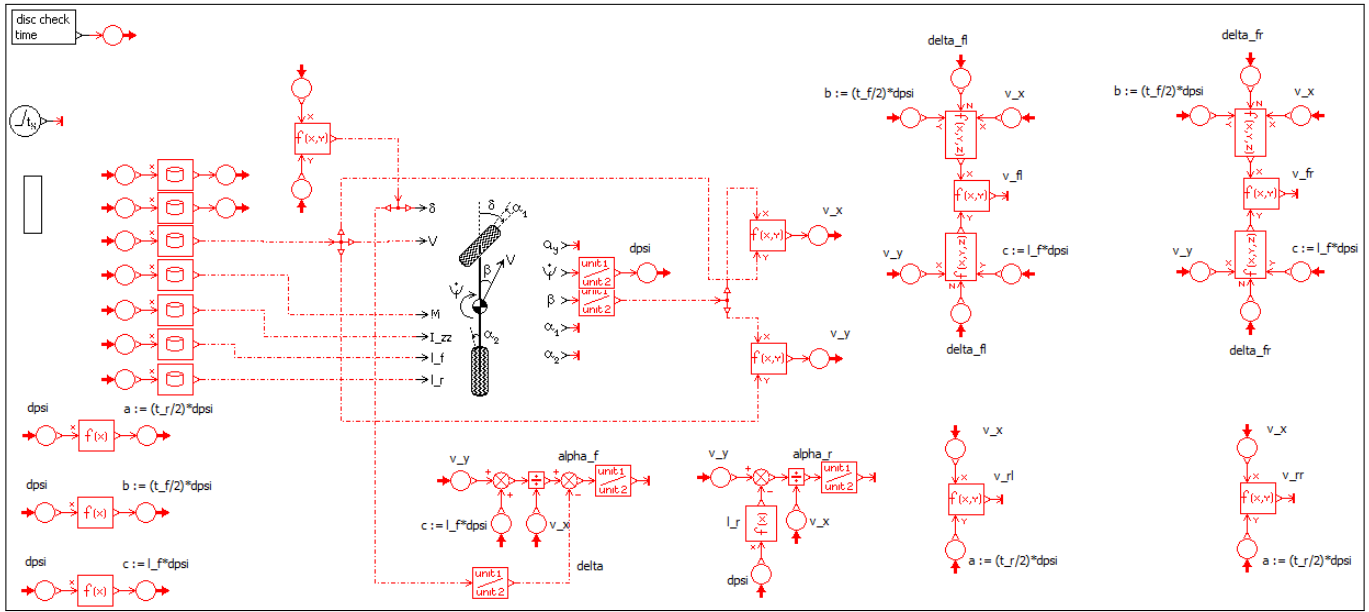


Fig. 2. Simcenter Amesim vehicle estimation model.

vehicle body (which also serve as measurement data), wheel force transducers (WFTs) measuring the three-dimensional rear wheel forces, optical sensor for vehicle body velocity and sideslip angle reference.

B. Test track

The test data has been recorded at the Ford Lommel Proving Ground's inner durability road 'Track 7', as shown in Fig. 4. The star marks start and finish of the lap, the blue dot indicates a cobblestone corner, and the red triangles highlight a hilly road section. The vehicle trajectory during the recording of the data selected for the case presented in this paper is highlighted in orange colour. Fig. 5 shows the vehicle behaviour during a part of the experimental test.

In this case the test data has been recorded during mild excitation of the vehicle dynamics, resembling a vehicle's daily driving on public roads.



Fig. 3. Full electric Range Rover Evoque test vehicle (Flanders Make).

C. Estimator tuning and estimation results

For the tuning of the process noise and measurement covariance matrices required for the EKF, denoted respectively as Q

TABLE I
TEST VEHICLE SPECIFICATIONS.

| | | Value | Unit |
|--|-------------|-------|-------------------|
| Body geometry | | | |
| Wheelbase | L | 2.675 | m |
| Distance between front axle and COG | l_f | 1.439 | m |
| Distance between rear axle and COG | l_r | 1.236 | m |
| Vehicle mass | m | 2,442 | kg |
| Yaw inertia | I_{zz} | 3,231 | kg m ² |
| Suspension, wheel, brake system | | | |
| Loaded tyre radius | r_l | 0.343 | m |
| Wheel rotational inertia | I_{whl} | 0.9 | kg m ² |
| Front proportional constant | $k_{brk f}$ | 36.3 | N m/bar |
| Rear proportional constant | $k_{brk r}$ | 9.2 | N m/bar |
| Powertrain | | | |
| Electric motor power, nominal | | 2×42 | kW |
| Electric motor torque, nominal | | 2×135 | Nm |

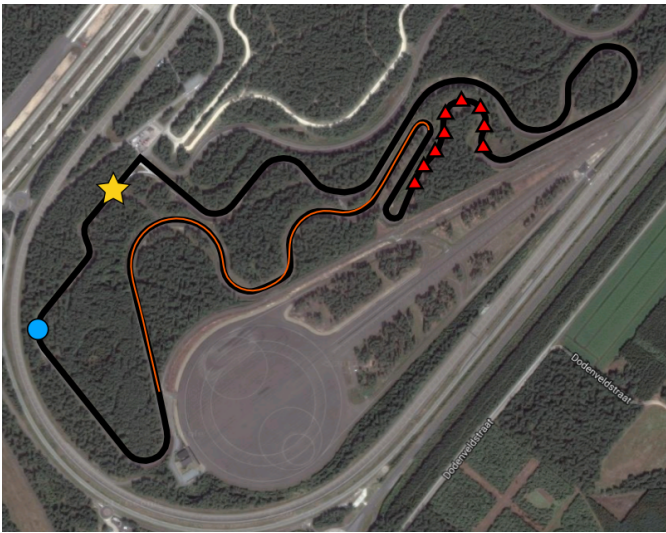


Fig. 4. Test track: ‘Track 7’ at Ford LPG.

and R , a rather straightforward approach was chosen as the focus is not on maximising estimation accuracy and robustness but on introducing the general concept of the overall estimation framework. The constant diagonal terms of the measurement noise covariance matrix \mathbf{R} are based on the actual signals’ RMS values. The process noise covariances are chosen as: $Q_{\dot{\psi}} = 1 \times 10^{-2} (\text{rad/s})^2$, $Q_{\psi} = 1 \times 10^{-2} \text{ rad}^2$, $Q_{\beta} = 1 \text{ deg}^2$, $Q_{x_{COG}} = 1 \times 10^{-2} \text{ m}^2$, $Q_{y_{COG}} = 1 \times 10^{-2} \text{ m}^2$.

In other cases extra robustness towards different levels of lateral dynamics excitation might be required. Then, for example, an adaptive estimation approach can be followed as proposed in [13].

Fig. 6 and Fig. 7 contain the estimation results for the longitudinal and lateral tyre forces, respectively, in direct comparison to the reference signals where applicable, that is, rear axle only.

For the longitudinal forces it is obvious that only the rear wheels were powered but all wheels were used for braking.

The reference signals are closely tracked by the estimation.

Looking at the lateral per-axle tyre forces, despite a small mismatch the reference is tracked well. This could be improved by more advanced estimator tuning or by making use of more complex estimation strategies. However, the usefulness of the overall estimation framework is positively proven by those results.

V. CONCLUSION

This work discussed the exploitation of a general purpose estimation toolbox and commercial 1D simulation software in order to set up automotive specific state-parameter estimators in a convenient and scalable fashion. The presented approach is validated experimentally on dynamic vehicle data, showing reliable results in line with state-of-the-art approaches. Future research will focus on comparing various models in this framework and evaluate their impact on the estimation accuracy.

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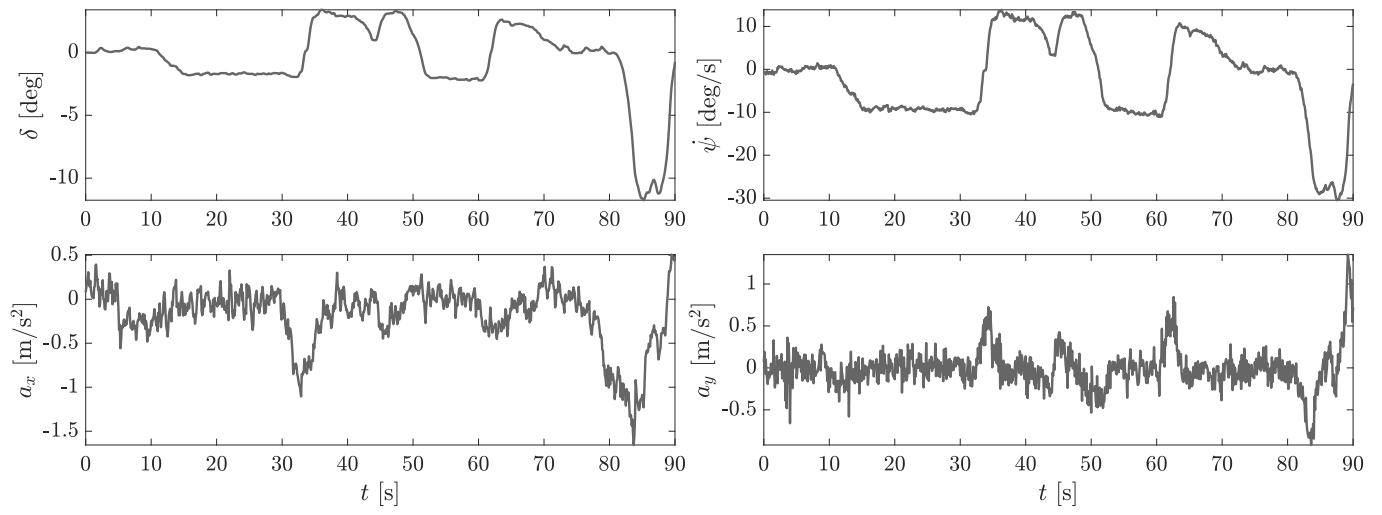


Fig. 5. Measurements.

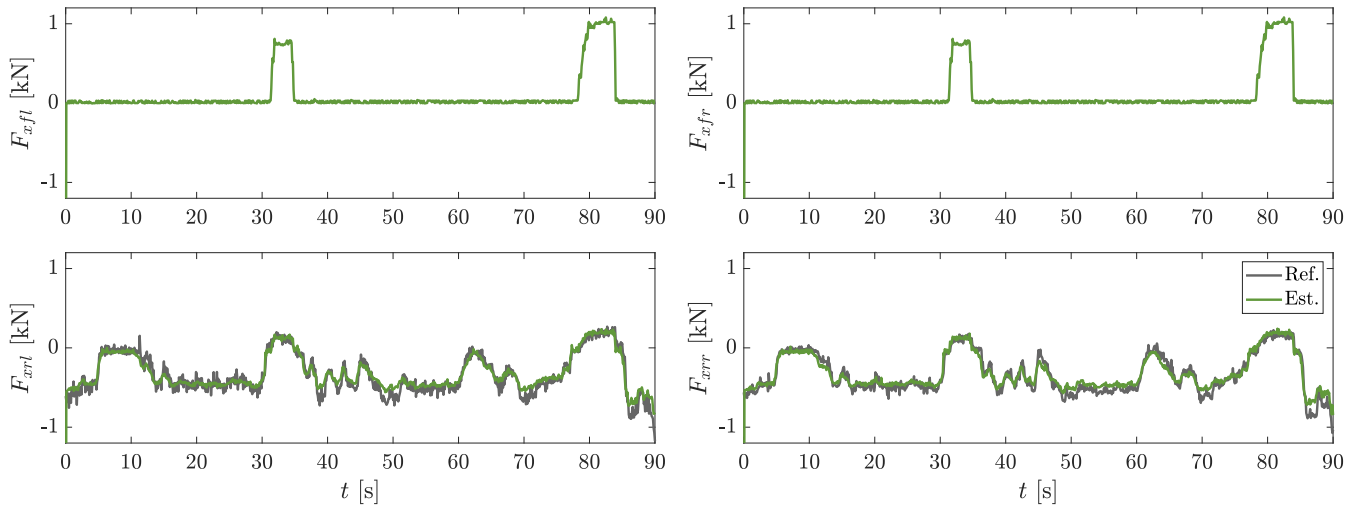


Fig. 6. Longitudinal tyre forces.

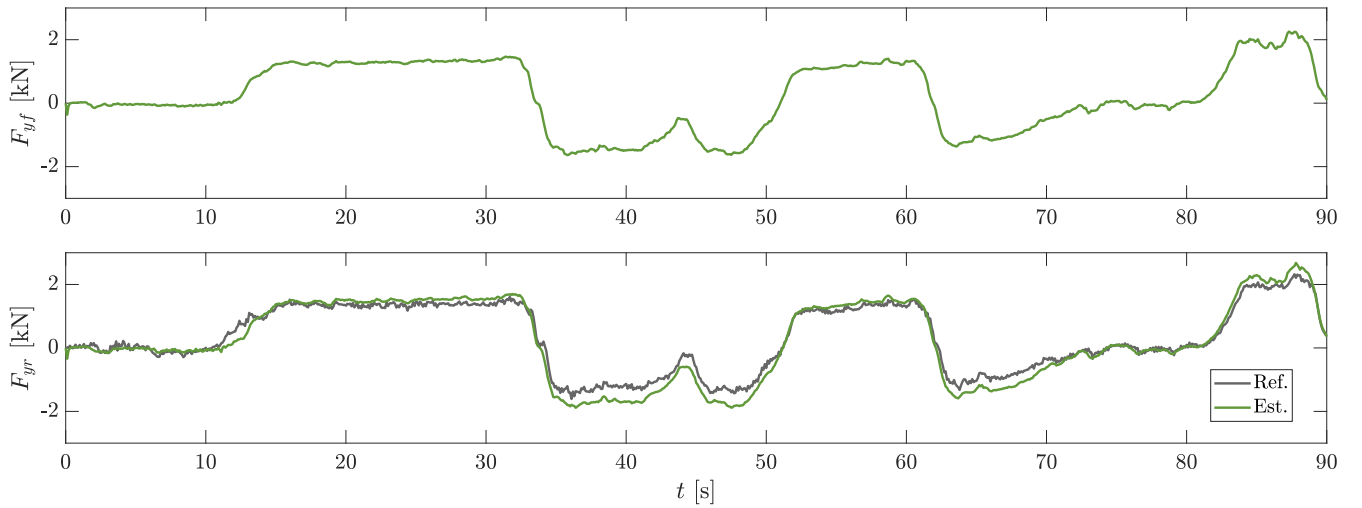


Fig. 7. Lateral tyre forces (per-axle).