

A Physical-Based Observer for Vehicle State Estimation and Road Condition Monitoring

LENZO, Basilio <<http://orcid.org/0000-0002-8520-7953>>, OTTOMANO, Giuseppe, STRANO, Salvatore, TERZO, Mario and TORDELA, Ciro

Available from Sheffield Hallam University Research Archive (SHURA) at:

<https://shura.shu.ac.uk/26859/>

This document is the Published Version [VoR]

Citation:

LENZO, Basilio, OTTOMANO, Giuseppe, STRANO, Salvatore, TERZO, Mario and TORDELA, Ciro (2020). A Physical-Based Observer for Vehicle State Estimation and Road Condition Monitoring. ICMCE 2020 conference proceedings. [Article]

Copyright and re-use policy

See <http://shura.shu.ac.uk/information.html>

PAPER • OPEN ACCESS

A Physical-Based Observer for Vehicle State Estimation and Road Condition Monitoring

To cite this article: B Lenzo *et al* 2020 *IOP Conf. Ser.: Mater. Sci. Eng.* **922** 012005

View the [article online](#) for updates and enhancements.

A Physical-Based Observer for Vehicle State Estimation and Road Condition Monitoring

B Lenzo¹, G Ottomano², S Strano², M Terzo² and C Tordela²

¹Sheffield Hallam University, United Kingdom

²University of Naples Federico II, Italy

Abstract. The performance of the vehicle's active safety systems depends on accurate knowledge of the vehicle state, and the frictional forces resulting from tyre contact and the road surface. This paper aims to estimate the vehicle states and tyre-road coefficient of friction through an Extended Kalman Filter (EKF), integrated with the Double-Track model and the Pacejka Magic Formula that allows knowledge of the lateral force of the tyre. Besides, this approach can estimate the overall coefficient of lateral friction on each side of the vehicle, left and right respectively. Simulations based on a reference vehicle model are performed on different road surfaces and driving manoeuvres to verify the effectiveness of the proposed estimation method, in order to obtain good performance from different vehicle control systems.

1. Introduction

Over the past decades driver assistance systems have become a standard in the automotive industry [1]. Nevertheless, the number of deaths caused each year in the world by road accidents exceeds one million. This number is unacceptable as technology and technology advances. In order to try to reduce this very high value, it is possible to try to improve the performance of these driver assistance systems. The performance of these systems could be further improved if more accurate knowledge on the vehicle state, inputs and parameters would be available. However, many of these variables, as the sideslip angle, cannot be measured directly in commercial vehicles because the sensors are very expensive. In literature, it's possible to distinguish mainly two approaches to develop vehicle state observers, that employing readily available sensors to correct the estimation of the variables which require the employment of expensive sensors. The first approach uses a kinematic vehicle model, independent from tyre parameters and road condition, in combination with measurement from standard vehicle sensors. This estimation technique is sensitive to sensor errors (noise and bias). A correction for these errors by GPS measurement is possible [2] [3], but requires accuracy is not achievable by consumer-grade GPS and reception may be lost.

The second approach uses a dynamic vehicle model in combination with the measurements from standard vehicle sensors. With this approach the model can correct for sensors inaccuracies and unwanted measurements, but information on tyre parameter and road condition is needed for the tyre model. Many observers have been developed based on this approach [4] [5] [6] [7] [8], where different tyre models have been used.

This paper proposes a new method for estimating the fundamental variables of vehicle dynamics and, at the same time, thanks to the use of a simple Magic formula characterized by four parameters obtained from extensive offline testing [9][10], the estimation of the lateral friction coefficient, through the use of an extended Kalman filter. The determination of interaction forces is a very complex operation, and as already mentioned, it requires the adoption of very expensive sensors. Through the approach proposed in this work a computationally slim method has been offered,



one that can be inserted inside a car control unit and therefore considerably reduce the cost of sensors on the vehicle. And in the final analysis to be able to allow to equip, any type of car, with high-performance safety systems and driving aid.

2. Estimator Design

The estimator is based on the Double-Track model. This model is shown in Figure 1 and Figure 2. The nomenclature used follows the following standard: the first subscript indicates the axle (front/rear), while the second subscript indicates the position (left/right). δ is the steering wheel angle; r is the yaw rate; V_G is the centre of gravity (COG) velocity vector, v and u are, respectively, the COG vehicle velocity components in lateral and longitudinal direction; β is the COG sideslip angle; $\alpha_{11} = \delta - atan\left(\frac{v+ra}{u-r\frac{t}{2}}\right)$, $\alpha_{12} = \delta - atan\left(\frac{v+ra}{u+r\frac{t}{2}}\right)$, $\alpha_{21} = -atan\left(\frac{v-rb}{u-r\frac{t}{2}}\right)$ and $\alpha_{22} = -atan\left(\frac{v-rb}{u+r\frac{t}{2}}\right)$ are respectively the front left, the front right, the rear left and the rear right tyre slip angles; F_{xij} and F_{yij} are the longitudinal and lateral tyre-road interaction forces; a and b are the distances from the COG to the front and rear axle; s is the vehicle track width; m is the vehicle mass and J is the yaw inertia moment. \dot{v} and \dot{r} represent the derivatives of v and r with respect to time.

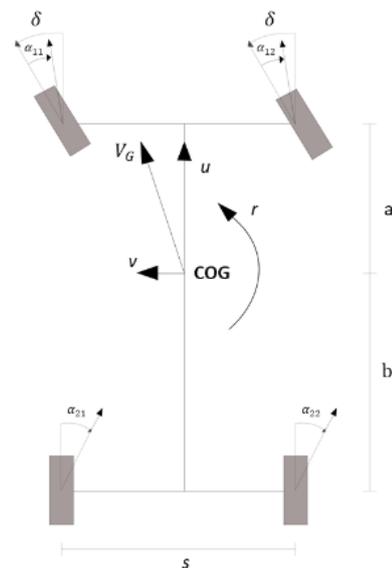


Figure 1. The Double-Track model: velocity vectors, slip angles and steering wheels angles.

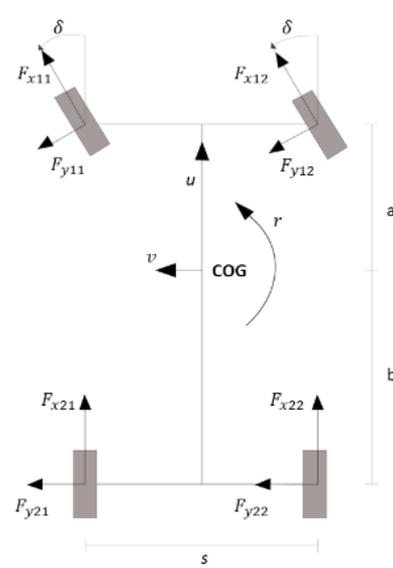


Figure 2. The Double-Track model: velocity vectors and pneumatic-road tangential interaction forces.

Table 1. List of vehicle main physical parameters.

Parameter name	Value
Vehicle mass	2217 kg
Distance from COG to front wheels	1.397 m
Distance from COG to rear wheels	1.663 m
Wheelbase	2.760 m
Height of COG	0.65 m
Yaw inertia moment	3231 kg/m ²
Track width	1.492 m

The lateral vehicle dynamic can be formulated as follow:

$$\begin{cases} \dot{v}_y = \frac{1}{m}(F_{y11} \cos \delta + F_{y12} \cos \delta + F_{y21} + F_{y22}) - ur \\ \dot{r} = \frac{1}{J}(F_{y11}a \cos \delta + F_{y12} \cos \delta a - F_{y21}b - F_{y22}b + F_{y11} \sin \delta \frac{S}{2} - F_{y12} \sin \delta \frac{S}{2}) \end{cases} \quad (1)$$

A four-parameter version of the Pacejka Magic Formula (stiffness factor B , form factor C , peak value D , curvature factor E) is used to model the tyre/road interaction forces to complete the dynamic vehicle description:

$$F_y(\alpha) = D \sin\{C \operatorname{atan}[B\alpha - E(B\alpha - \operatorname{atan}(B\alpha))]\} \quad (2)$$

The parameter D is placed equal to the product between the global lateral friction coefficient and the vertical load, respectively equal to $\mu_l F_z$ for the left side of the vehicle, and equal to $\mu_r F_z$ for the right side, obtaining two different formulations of the Pacejka Magic Formula (MF). Considering the global lateral friction coefficients represented by the following equation

$$\dot{\mu}_l = 0; \dot{\mu}_r = 0 \quad (3)$$

as additional states of an augmented state vector [11], the estimator design model is obtained. The state vector is given by $\mathbf{x} = [v, r, \mu_l, \mu_r]^T$ where v is the lateral velocity, r is the yaw rate, and μ_l and μ_r are the lateral coefficients of adhesion left and right respectively. The input vector $\mathbf{u} = [\delta, u]^T$ is composed by the steering wheel angle δ and the longitudinal speed of the vehicle u . The EKF estimation algorithm is briefly recalled in Figure 3 [11]. Consider the nonlinear state function \mathbf{f} given by the combination of the equations (1) – (3) with an additive Gaussian process noise \mathbf{w} and a nonlinear function \mathbf{h} of measurement equations with an additive Gaussian noise \mathbf{v} :

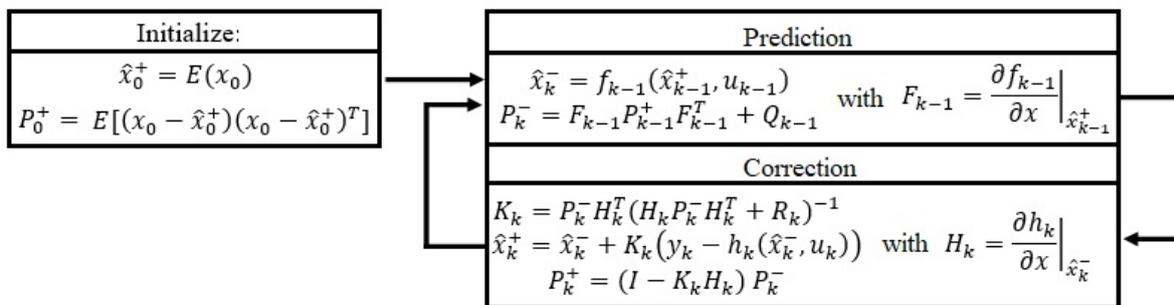


Figure 3. EKF estimation algorithm

Diagonal and constant process noise covariance Q_{k-1} and measurement noise covariance R_k matrices are considered. In the estimator design model outlined above, the estimated measurements vector is constituted by the lateral acceleration and the yaw rate:

$$\hat{\mathbf{y}} = \begin{bmatrix} \hat{a}_y \\ \hat{r} \end{bmatrix} = \begin{bmatrix} \dot{v} + ur \\ r \end{bmatrix} \quad (4)$$

This vector is compared with the real measurements vector coming from the vehicle to perform the updating operation of the estimated states and the error covariance. The suitability of the EKF estimator for the proposed application is demonstrated for two case studies.

3. Simulation Results

The simulations results presented in this section are obtained using Matlab/Simulink. A comparison was made between the estimator and a full-vehicle model obtained through the software Adams/Car.

The sideslip angle, the left and right coefficient of frictions and the measurements of the reference vehicle are compared with the estimation provided by the EKF. In order to obtain realistic measurements, Gaussian noises are added in the simulated measurements. The simulation results of two representative manoeuvres are presented here. Table 2 gives the details and purpose of each manoeuvres. Figure 4 provides the indicative physical representation of each proposed scenario where the colour represents the friction coefficient. The black colour corresponds to a high friction value; the green colour corresponds to a medium friction value; and the green colour corresponds to a low friction value. The change in friction is time-dependent and occurs at successive time intervals. During simulations, the system is set on an equilibrium point with constant longitudinal velocity

Table 2. Details and investigative purpose of each simulated manoeuvres.

Simulated manoeuvres	Test Surface	Purpose
Step steer – case 1: step varying μ for all tyres	Five levels of global lateral friction coefficient with unequal step sizes	Determinate the estimator response to a quick change in road surface. Friction coefficient is varied at five new levels.
Step steer – case 2: different step varying μ for left/right tyres	Each wheel is subjected simultaneously to two different frictions	Validate the TRFC detection under small friction variations. Also, each wheel is exposed to different surface at the same time (distinct μ for the left and right tyres)

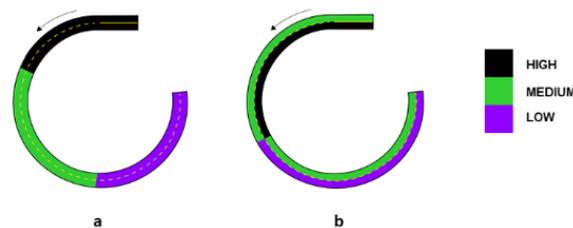


Figure 4. Schematic road layout with time-dependent changing of global friction coefficient.

3.1. Step Steer Manoeuvre: case 1

In this configuration, Figure 4a, a decreasing trend of the tire-road friction coefficient has been imposed. Transitions occur during successive equal time intervals of 10 seconds. A 0 – 100 deg change in the steering angle of the front left and right tires have been imposed. The longitudinal speed is set to 60 km/h. The estimator behaviour is represented by the measurements vector and the sideslip angle, Figure 5; the global left and right lateral friction coefficient, Figure 6; the lateral forces, Figure 7, and the normal, Figure 8, forces of the tire.

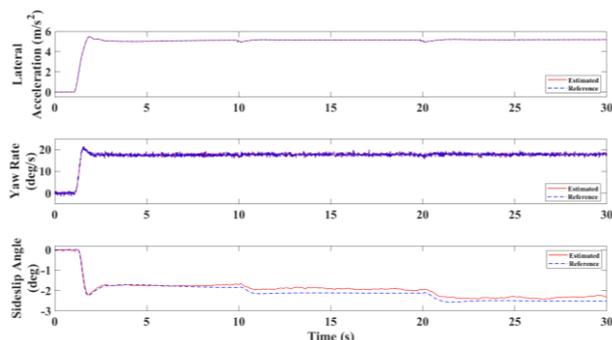


Figure 5. Measurements Vector and Sideslip Angle: Step steer case 1.

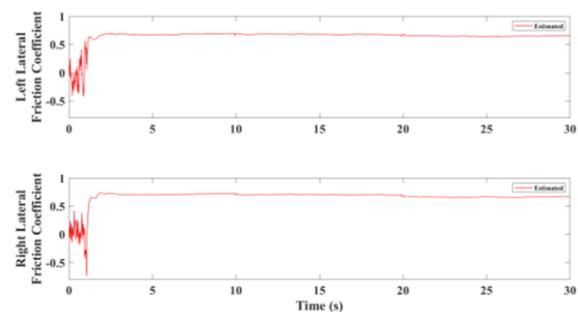


Figure 6. Left and Right lateral global friction coefficient in a time varying friction scenario.

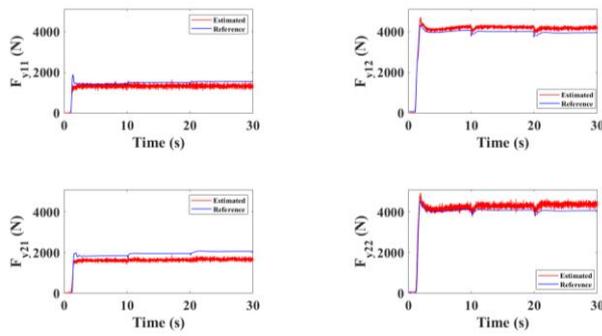


Figure 7. Lateral forces of the tyre: Step steer case 1.

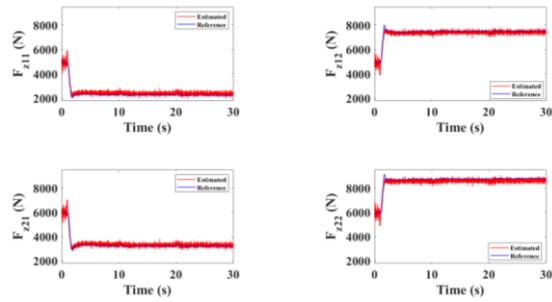


Figure 8. Normal forces of the tyre: Step steer case 1.

This simulation allows appreciating how the estimator reacts to successive variations of the global lateral friction coefficient. It is possible to observe three different variations of this latter value that occur every 10 seconds. The estimator manages, in an excellent way, to provide an estimation of the value of the global lateral friction coefficient and the vehicle states.

3.2. *Step Steer Manoeuvre: case 2*

While case 1 showed an equal change for all the wheels, here, the tyre-road friction coefficient is set at two different levels for the left and the right side of the vehicle, Figure 4b. The transition occurs during an equal time interval of 10 seconds. A $0 - 100 \text{ deg}$ change in the steering angle of the front left and right tires have been imposed. The longitudinal speed is set to 60 km/h . The estimator behaviour is represented by the measurements vector and the sideslip angle, Figure 9; the global left and right lateral friction coefficient, Figure 10; the lateral forces, Figure 11, and the normal, Figure 12, forces of the tire.

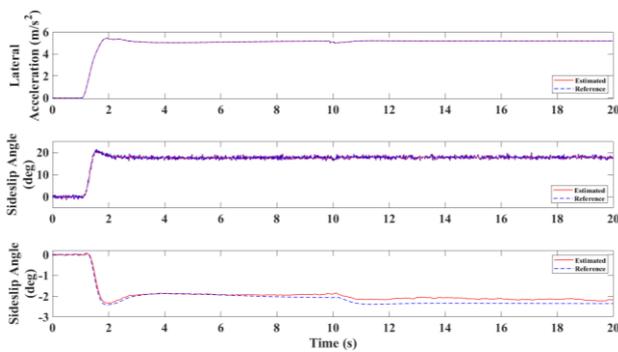


Figure 9. Measurements Vector and Sideslip Angle: Step steer case 2.

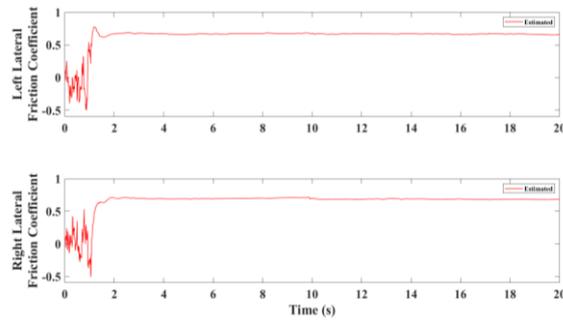


Figure 10. Left and Right lateral global friction coefficient in a time varying friction scenario with different friction for each side of the vehicle.

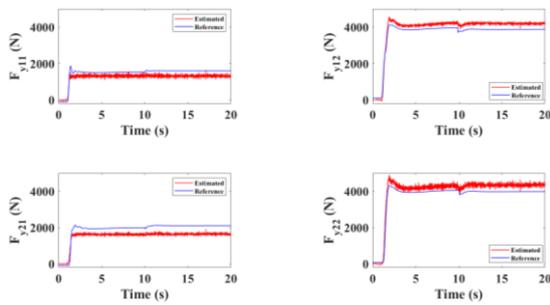


Figure 11. Lateral forces of the tyre: Step steer case 2.

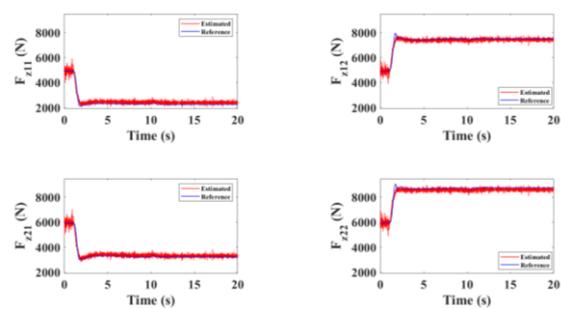


Figure 12. Normal forces of the tyre: Step steer case 2.

This simulation highlights a different peculiarity of the EKF. The estimator is able to detect a different value of the global lateral coefficient of friction on the two different sides of the vehicle and manages to detect the small variation in friction that occurs at 10 seconds. In both situations, the employed approach provides an excellent estimation of the vehicle conditions.

4. Conclusions

An Extended Kalman Filter has been proposed for the estimation of the lateral friction coefficient and the state of the vehicle. The procedure provides a reliable estimation of the state of the system and a consistent identification of the lateral friction coefficient. The EKF has been compared to a full-vehicle Adams/Car model, these simulation results are the first step in the model validation. This estimation can be used to improve the performance of the vehicle's active safety systems, as well as to monitor real-time changes in road conditions. A possible future development is its implementation in an onboard real-time system.

5. References

- [1] Bosch R 2014 Bosch Automotive Handbook 9th ed.
- [2] Ryu J and Gerdes J C 2004 Integrating inertial sensors with gps for vehicle dynamics control *Journal of Dynamic Systems, Measurement, and Control* 243–254.
- [3] Strano, S., Terzo, M. Constrained nonlinear filter for vehicle sideslip angle estimation with no a priori knowledge of tyre characteristics (2018) *Control Engineering Practice*, 71, pp. 10-17.
- [4] Strano, S., Terzo, M. Vehicle sideslip angle estimation via a Riccati equation based nonlinear filter (2017) *Meccanica*, 52 (15), pp. 3513-3529.
- [5] Farroni, F., Lamberti, R., Mancinelli, N., Timpone, F. TRIP-ID: A tool for a smart and interactive identification of Magic Formula tyre model parameters from experimental data acquired on track or test rig, *Mechanical Systems and Signal Processing*, 102, pp. 1-22.
- [6] Farroni, F, T.R.I.C.K.-Tire/Road Interaction Characterization & Knowledge - A tool for the evaluation of tire and vehicle performances in outdoor test sessions. *Mechanical Systems and Signal Processing*, 72-73, pp. 808-831.
- [7] Boulkroune B, v Aalst S, Rademakers E, Sannen K and Ghouti N E 2015 Vehicle sideslip angle estimation using nonlinear parameter-varying observers In 2015 Int. Automatic Control Conference 108–113.
- [8] Farroni, F., Pasquino, N., Rocca, E., Timpone, F. A comparison among different methods to estimate vehicle sideslip angle. *Lecture Notes in Engineering and Computer Science*, 2018, pp. 1084-1090.
- [9] Pacejka H B 2006 *Tyre and Vehicle Dynamics*, 2nd ed.
- [10] Tass “Tyre testing,” <https://www.tassinternational.com/tyre-testing>.
- [11] Simon D 2006 *Optimal State Estimation: Kalman, H_∞ and nonlinear approaches*. J. Wiley and Sons, New York