State and input observer for the multibody model of a car

Emilio Sanjurjo[1], Antonio J. Rodríguez[1], Daniel Dopico[1], Alberto Luaces[1] and Miguel Ángel Naya[1]

[1]*Mechanical Engineering Laboratory, Universidade da Coruña (University of A Coruna), emilio.sanjurjo@udc.es*

Road safety continues to be a major concern, since more than 1.2 million people die every year due to road traffic injuries, being also the main cause of mortality among people aged 15-29 years [1]. This fact has motivated an intense research effort to increase both active and passive safety in road vehicles. The advanced driving aid systems (ADAS) have contributed to avoid accidents, and it is expected that the autonomous vehicles will be even safer. However, these systems require huge amounts of data about the state of the vehicle and its environment. This leads to vehicles with many sensors to monitor any magnitude of interest.

Nevertheless, some pieces of information cannot be measured directly due to economic or technical constraints. When this happens, the required magnitudes have to be inferred from the measurements which are available and mathematical models of the system of interest.

This work aims to evaluate the performance of an indirect Kalman filter at estimating states (positions and velocities) and inputs (forces) when applied to the multibody model of a vehicle. In order to be able to control all the variables, all the tests rely on simulations. Therefore, we built one multibody model which plays the role of the *real* system. More details of this model can be seen in [2]. Sensor measurements are generated from this model, and Gaussian noise is added to build sensor signals with realistic properties. The sensors considered in this work are listed in table 1.

Measured magnitudes	**Sensor**	**Sampling rate (Hz)**	**Noise variance**	**Function**
Vehicle accelerations (X,Y,Z)	Accelerometers	250	0.447 m/s^2	Observer output
Vehicle angular rates (X,Y,Z)	Gyroscopes	250	0.011 rad/s	Observer output
Wheel rotation angles	Hall-effect sensors	250	0.078 rad	Observer output
Brake line pressure	Pressure sensor	250	—	Multibody input
Steering wheel angle	Encoders	250	—	Multibody input
Rear wheel torque	Wheel torque	250	—	Multibody input
Position, speed and course	GPS receiver	5	1.785 m, 0.053 m/s	Observer output

Tab. 1: List of installed sensors and their properties.

The second multibody model is similar to the previous one, but it has some differences, as if they were modeling errors. In this example, the mass of the chassis of the *imperfect model* has 100 kg in excess, compared to the mass of the *real* chassis. This model is used as the plant of the state observer.

The third system is the *observer*, which uses an error-state extended Kalman filter [3] (also known as indirect extended Kalman filter) to combine information from the dynamics of the second model (i.e. the *imperfect model*) with the noisy measurements built from the *real* model. The simplified structure of this observer is shown in fig. 1, where the estimation algorithm used is this work is referred to as errorEKF_FE. This algorithm is an evolution of the errorEKF method presented in [4].

The results obtained so far from this method are promising. Some results of force estimation at the right front wheel are shown in Figs. 2a and 2b, and position estimation is shown in Figs. 2c and 2d. It is remarkable that this algorithm can estimate forces in parts of the mechanism where there are neither accelerometers nor force sensors. The position estimation error was 0.15 m root mean squared error (RMSE), while the GPS used provides an error of 1.775 m RMSE. However, in its current state, the method is not robust enough to be used in real applications. Moreover, the results are greatly conditioned by the values given to the covariance matrices of the plant and measurement noise, so either a systematic approach to adjust them, or an adaptive Kalman filter seem necessary.

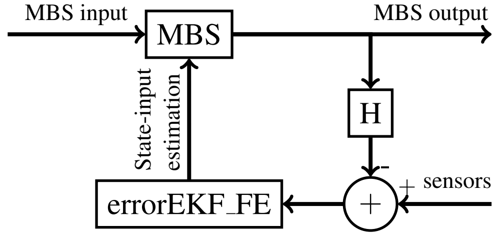
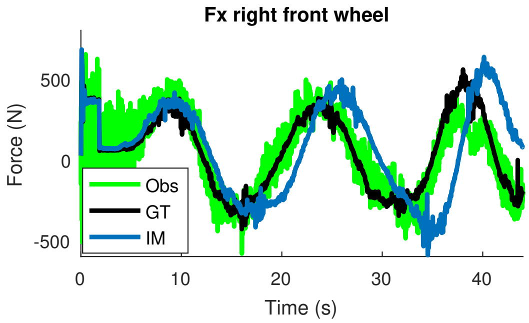
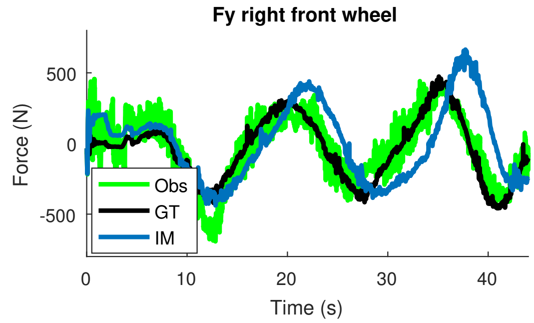


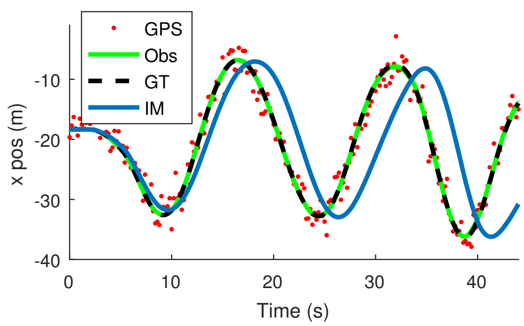
Fig. 1: Simplified flow diagram of the error state Kalman filter applied to multibody simulations



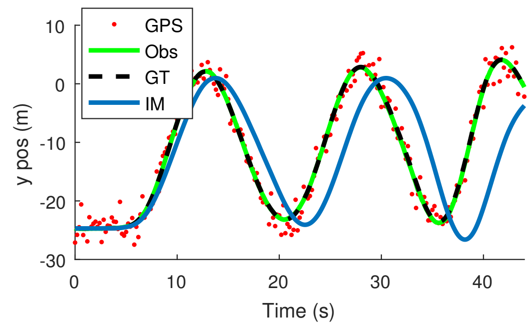
(a) Force estimation in x direction in right front wheel



(b) Force estimation in y direction in right front wheel



(c) Position estimation in x



(d) Position estimation in y

Fig. 2: Results provided by the state observer, where Obs is the *observer*, GT (ground truth) is the *real* mechanism, and IM in the *imperfect model*.

Acknowledgments

This work has been partially financed by the Spanish Ministry of Economy and Competitiveness (MINECO) and EU-ERDF funds under the projects ‘Observadores de estados y entradas basados en modelos multicuerpo detallados aplicados al control de vehículos’ (TRA2014-59435-P) and ‘Diseño y control óptimo eficiente de sistemas multicuerpo basado en técnicas de análisis de sensibilidad’ (DPI2016-81005-P), and by the Galician Government through grant ED431B2016/031.

References

[1] W.H.O., “Global status report on road safety 2015,” 2015.

[2] R. Pastorino, E. Sanjurjo, A. Luaces, M. A. Naya, W. Desmet, and J. Cuadrado, “Validation of a real-time multibody model for an X-by-wire vehicle prototype through field testing,” *Journal of Computational and Nonlinear Dynamics*, vol. 10, p. 031006, may 2015.

[3] P. D. Groves, *Principles of GNSS, inertial, and multisensor integrated navigation systems*. Boston/London: Artech House, 2 ed., 2013.

[4] E. Sanjurjo, M. Á. Naya, J. L. Blanco-Claraco, J. L. Torres-Moreno, and A. Giménez-Fernández, “Accuracy and efficiency comparison of various nonlinear Kalman filters applied to multibody models,” *Nonlinear Dynamics*, vol. 88, pp. 1935–1951, may 2017.