# Indirect State and Force Estimator Based on Multibody Models

Emilio Sanjurjo, Miguel Á. Naya, Daniel Dopico, Antonio J. Rodríguez

Laboratorio de Ingeniería Mecánica
University of A Coruña
C/ Mendizábal s/n, 15403, Ferrol, Spain
[emilio.sanjurjo, minaya, ddopico, antonio.rodriguez.gonzalez]@udc.es

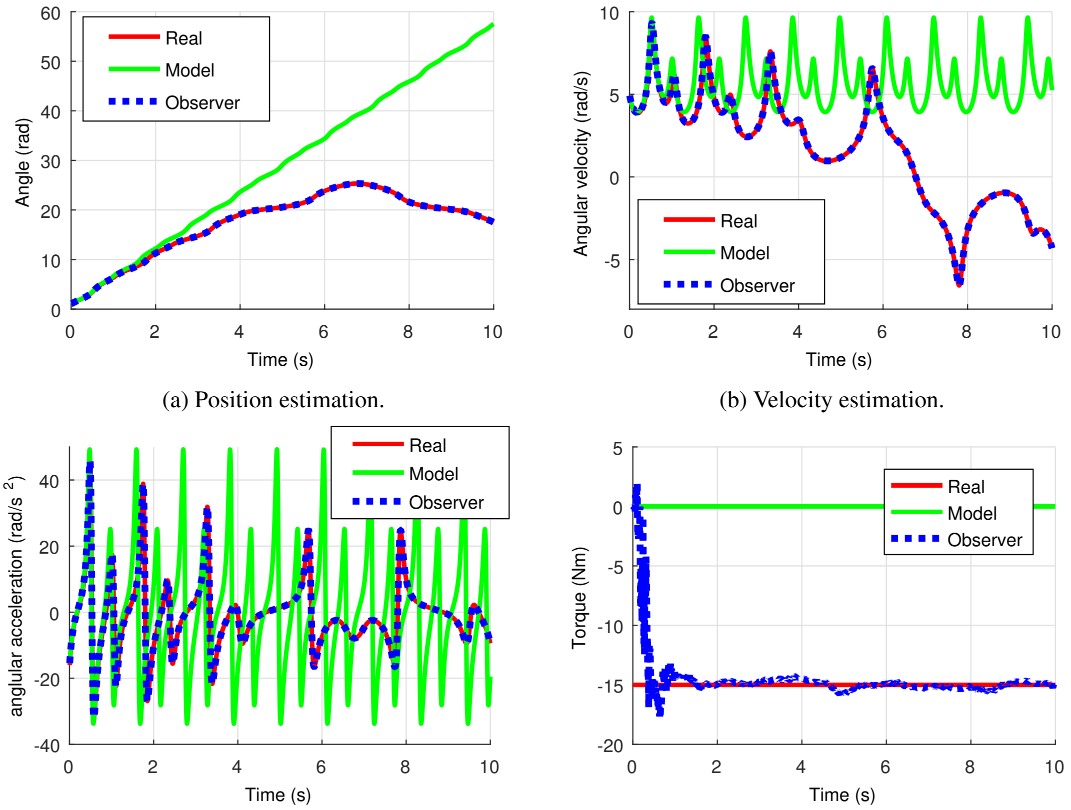
## Abstract

Multibody simulations have already been used for a long time to reduce development time and cost in many sectors of the industry [1]. Although the first applications of multibody simulations were aimed at predicting the dynamic behavior of machines and/or mechanisms, the efficiency of the multibody formulations developed during the last years, combined with the increasing computational power available, have allowed new applications for multibody simulations, such as human-in-the-loop and hardware-in-the-loop simulations, which require real-time execution [2, 3].

During the last decade, some research groups started to employ multibody dynamics techniques to devise state observers [4, 5, 6, 7]. The advantages of this strategy with respect to state observers designed in a more conventional way are the accuracy of the multibody models with respect to simplified closed-form models, and the general methodology provided by the multibody formulations to develop models of new systems and sensors. Moreover, multibody models usually provide more information, which is usually neglected when using a closed-form model.

The main drawbacks of using multibody simulations for state observers include their high computational cost, not allowing to employ unscented Kalman filters in problems of moderate size, and the lack of accuracy of the force models employed.

Some of these problems can be overcome by using simple kinematic models, but at the cost of adding acceleration sensors to provide the input to the kinematic model [8, 9]. If the extra sensors are not available, then a dynamical model has to be used. However, if the force models are not accurate enough, the prediction of the model




(a) Position estimation. (b) Velocity estimation.

(c) Acceleration estimation. (d) Force estimation.

Figure 1: Estimation results from the test with the four-bar linkage. Plots (a) to (c) show the crank angle, angular velocity, and angular acceleration, while plot (d) shows the estimation of the torque applied to the crank.

will be biased. Although accurate results can be obtained with this approach if the values of the plant noise are properly adjusted [10], correcting the plant by estimating the actual force applied to the system should provide a more accurate solution. In some problems the force estimation can be the main aim, independently of the kinematic magnitudes.

In this work, an indirect Kalman filter estimating position, velocity and acceleration errors of a multibody simulation is proposed. The name *indirect* comes from the fact that the method does not estimate the magnitudes of interest, but the errors that the multibody model makes in tracking the real system. The acceleration errors are employed to calculate the force errors which would avoid the drift of the model, and these forces are applied to the model. Moreover, the kinematic magnitudes previously estimated are also corrected. This approach allows to obtain accurate state estimations, while estimating also the unknown forces.

In order to evaluate the behavior of this approach, two multibody models are employed. The first one is considered as the real mechanism. Its motion is measured with one or more sensors, which are corrupted by noise to simulate real sensors. The second multibody model acts as a model of the first one. They are similar, but there are some differences as if they were modeling errors, such as those produced due to unknown forces or parameters, or due to simplified force models. Finally, a state observer is built using the second multibody model and correcting it with information provided by the noisy measurements taken from the first model (the "real mechanism").

This methodology has been applied in this work to a four-bar and a five-bar linkages. The mechanisms considered as real have constant torques applied to their cranks, while their corresponding models do not have any applied torque, thus simulating a situation in which the actual forces are unknown.

The results obtained from a test with the four-bar linkage can be seen in Figure 1. In this test, the real mechanism has a -15 Nm torque applied to its crank, while this torque is unknown to the model and the state observer. The only sensor considered for this test was an encoder measuring the crank angle. The results show how the errors in the multibody model make it diverge from the behavior of the real mechanism, while the state observer properly tracks both the kinematic magnitudes and the torque applied at the crank.

## Acknowledgments

This work has been partially financed by the Spanish Ministry of Economy and Competitiveness 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). The research of Antonio J. Rodríguez was founded by fellowship BES-C-2015-0014 of Spanish Government.

## References

[1] P. Eberhard, W. Schiehlen. Computational Dynamics of Multibody Systems: History, Formalisms, and Applications. Journal of Computational and Nonlinear Dynamics, 1:3–12, 2006.

[2] R. Pastorino, F. Cosco, F. Naets, W. Desmet, J. Cuadrado. Hard real-time multibody simulations using ARM-based embedded systems. Multibody System Dynamics, 37:127–143, 2016.

[3] J. García de Jalón, E. Bayo. Kinematic and Dynamic Simulation of Multibody Systems: The Real Time Challenge. Springer-Verlag, 1994.

[4] J. Cuadrado, D. Dopico, A. Barreiro, E. Delgado. Real-time state observers based on multibody models and the extended Kalman filter. Journal of Mechanical Science and Technology, 23:894–900, 2009.

[5] R. Pastorino, D. Richiedei, J. Cuadrado, A. Trevisani. State estimation using multibody models and non-linear Kalman filter. International Journal of Non-Linear Mechanics, 53:83–90, 2013.

[6] F. Naets, R. Pastorino, J. Cuadrado, W. Desmet. Online state and input force estimation for multibody models employing extended kalman filtering. Multibody System Dynamics, 32:317–336, 2014.

[7] J. L. Torres-Moreno, J. L. Blanco-Claraco, A. Giménez-Fernández, E. Sanjurjo, M. Á. Naya. Online Kinematic and Dynamic-State Estimation for Constrained Multibody Systems Based on IMUs. Sensors, 16:333, 2016.

[8] I. Palomba, D. Richiedei, A. Trevisani. Kinematic state estimation for rigid-link multibody systems by means of nonlinear constraint equations. Multibody System Dynamics, 40:1–22, 2017.

[9] I. Palomba, D. Richiedei, A. Trevisani. Two-stage approach to state and force estimation in rigid-link multibody systems. Multibody System Dynamics, 39:115–134, 2017.

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