An FMI-based Framework for State and Parameter Estimation

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In many applications, after the system has been designed, controls and/or fault detection and diagnostics (FDD) algorithms are developed and deployed. These techniques should be able to leverage the models developed during the earlier design stages, thereby increasing the productivity of the overall product development. Advanced control (such as adaptive control or model predictive control) and FDD techniques require an enhanced knowledge of the system state. For example, the flight controller of an airplane should try to estimate the real velocity and position of the aircraft while compensating for measurements errors and sensor noises. When dealing with dynamic system, having an enhanced knowledge about the system state means estimating its state variables with associated error bounds.

This paper proposes a solution for creating a model-based state estimator for dynamic systems described using the FMI standard. This work extends the capabilities of any modeling framework compliant with the FMI standard version 1.0. The FMI is a standard that allows to embed a simulation model within a unified interface in order to couple simulation models developed using different simulation programs. Although the FMI standard has been created mainly for co-simulation, we leverage this standard for providing an algorithm that is compatible with a large number of simulation and modeling platforms, including Modelica-based ones.

The state estimation technique used in this work is the unscented Kalman filter (UKF) [1, 2]. The UKF is able to deal with nonlinear systems and it just requires to perform function evaluations of the model in order to compute the evolution of its state variables and the value of its outputs. The UKF has less requirements about the knowledge of the model with respect to other nonlinear state estimation techniques. For example the extended Kalman filter needs to linearize the model [3]. The computational performances of the UKF are modest with respect to other Monte Carlo based techniques (like particle filters [4]), enabling its use for real-time applications.

References

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