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A fast and versatile technique for constrained state estimation

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ABSTRACT

In situ adaptive tabulation or ISAT based moving horizon estimation (MHE) is suggested as a fast and robust approach for state estimation. Computational issues with a moving horizon constrained state estimation technique like MHE are discussed. Implementation of storage and retrieval approach of ISAT for state estimation is proposed to maintain the accuracy and robustness of MHE, while generating the estimates at a reduced computational cost (~300 times faster). Comparison with the widely used nonlinear state estimation technique of extended Kalman filtering (EKF) shows better performance using ISAT–MHE. Case studies with nonlinear discrete-time and continuous-time systems are carried out using ISAT, which is tailored for solving the optimal estimation problem.

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1. Introduction

Estimation of model parameters and states is an integral part of process modeling, monitoring and control strategies. Data from most chemical processes are corrupted by process and/or measurement noise. In practice, online measurements of all the state variables of a process are rarely available. For these systems the state(s) cannot be measured explicitly. Hence, a robust state estimation technique is required that estimates the unmeasured states from output measurements by negating the influence of measurement noise. State estimators use deterministic or stochastic, and static or dynamic approaches to provide approximate estimate of state variables in real-time and must rely on a mathematical process model to function online. Depending on the nonlinearity of the model, computational time may become an issue in state estimation for large-scale systems.

For a good state estimator under nominal conditions of no model-plant mismatch or unmeasurable disturbances, the difference between the actual and estimated states asymptotically decays to zero [1]. State estimation methods combine the knowledge of the *a priori* model with available measurements to estimate the states in real-time. Different approaches for state estimation have been used previously for linear and nonlinear systems, as discussed in the next section.

2. Techniques for state estimation

The choice of a state estimation technique to a large extent depends on the type of process under consideration (linear or nonlinear). For a linear system, there exists only one optimal estimate of the state when the system is observable. On the other hand, for nonlinear systems there can be many locally optimal state estimates. The properties of observability and detectability are of great importance for state estimator design [1]. Detectability is a necessary and sufficient condition for state estimation and observability of a process is a sufficient condition.

The conditional probability density of the state, given the measurements, is the statistical distribution of interest for any estimation algorithm [2]. For linear systems with Gaussian noise, this conditional density is also Gaussian with mean and covariance given by the widely used Kalman filter (KF), which provides a recursive solution to the minimum-variance state estimation problem [3]. For nonlinear systems, in general the conditional density is not Gaussian and a different state estimation technique has to be employed to attempt reconstruction of the conditional density. Extension of KF to unconstrained nonlinear systems using successive linearization leads to the extended Kalman filter (EKF), which has received considerable attention in the past. Another modification to the KF formulation makes use of minimal set of sample points around the mean. This technique avoids explicit computation of the Jacobian and is called the unscented Kalman filter (UKF), based on the unscented transform it uses to obtain the sample points. A different class of nonlinear filters that approximate the complete non-Gaussian probability density of the states using the measurements is the particle filter (PF). Finally, a more robust (although computationally intensive) approach for state estimation in nonlinear models with inequality constraints involves solving a real-time optimization problem over a moving window of measurements and is known as moving horizon estimation (MHE). The next section deals with the formulation of the most widely used technique for nonlinear state estimation (EKF) and discusses its relative advantages

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