Introduction to Filtering and Estimation

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Process states are the variables that specify uniquely the state of a process at any given time, reliable and real-time information on which are essential to effective process operation. However, some process states are rarely available on-line and can be only obtained by laboratory analysis, such as product composition, molecular weight distribution, melt index and Kappa number. Therefore, state estimation is required to determine estimates of the unmeasurable states given the state-space model, a priori initial state estimates, and a sequence of process data measured up to and including current time.

State estimation has many applications in process control, performance monitoring, fault detection, and data reconciliation. The well-known Kalman filter (KF) provides optimal state estimates for linear systems in the presence of Gaussian disturbances. However, the practical systems always exhibit nonlinear dynamics and subject to non-Gaussian noises. State estimation of such nonlinear systems is out of the capability of KF. To solve this problem, many suboptimal approaches have been developed, including extended Kalman filter (EKF), unscented Kalman filter (UKF), particle Filter (PF) and moving horizon estimation (MHE).

- The EKF is probably the most widely used state estimation methods for nonlinear systems. It is designed by first-order linearization of nonlinear functions in the state and measurement equations so that classical KF is applicable. However, EKF suffers from several inherent limitations, i.e., 1.) the calculation of Jacobians is nontrivial in many applications; 2.) first-order linearization may lead to divergence or poor approximation when the system is severely nonlinear; 3.) it is only accurate up to the first order in estimating mean and covariance.

- Instead of approximating the nonlinear functions, the UKF utilizes a set of deterministically chosen "sigma points" and associated weights to approximate the posterior mean and covariance of the Gaussian random variable with a second order accuracy. The idea is to propagate the sigma points through the nonlinear functions, and then update the state estimate based on the transformed points and the measurement information. The UKF is easy to implement because it does not require calculation of Jacobians. Furthermore, it can provide superior performance to EKF with no increase in computational complexity.

- The PF approximates the posterior density function by a weighted set of random particles. It is suitable for general nonlinear and non-Gaussian systems since no simplification of nonlinearity or assumption of explicit density are necessary. The PF with infinity particles can provide asymptotically optimal state estimates, but a major disadvantage of which is the computational complexity. The phenomena of degeneracy and impoverishment is another challenge problem, which must be considered when applying PF to practical systems. Moreover, PF is more sensitive to a poor initial guess, it requires much longer recovery time than other filtering algorithms.

- The MHE formulates state estimation as an optimization problem defined over a fixed-length moving horizon, which provides a good framework to handle state constraints. To incorporate previous information for approximating the full information problem, calculation of the arrival cost is required in MHE at each time step. This practice may not only increase the computational cost but also limit the estimation performance. Additionally, how to get the best approximation of arrival cost is still an open issue. For online implementation of MHE, choice of the horizon is a tradeoff between the accuracy requirement and the available computational resource.

Although considerable research efforts have been devoted to investigating state estimation of nonlinear systems, many unsolved theoretical and practical problems still remain in this area. Examples of the open problems are:

- How to evaluate the estimation performance and prove the global convergence of the estimator analytically.

- How to reduce the computational load of the existing nonlinear state estimation methods for online implementation.

- How to achieve robust state estimation in the presence of outlier, missing measurement, uncertain time delay and model parameter uncertainty.

- How to incorporate infrequent and delayed primary measurements with frequent secondary measurements to improve the estimation performance especially in the presence of model-plant mismatch and unmeasured disturbance.

- How to solve state estimation problem of nonlinear systems with linear or nonlinear equality or inequality constraints, hybrid systems with both discrete and continuous states, switching systems with multiple operating modes.