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Identification of process and measurement noise covariance for state and parameter estimation using extended Kalman filter

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ABSTRACT

The performance of Bayesian state estimators, such as the extended Kalman filter (EKF), is dependent on the accurate characterisation of the uncertainties in the state dynamics and in the measurements. The parameters of the noise densities associated with these uncertainties are, however, often treated as 'tuning parameters' and adjusted in an ad hoc manner while carrying out state and parameter estimation. In this work, two approaches are developed for constructing the maximum likelihood estimates (MLE) of the state and measurement noise covariance matrices from operating input–output data when the states and/or parameters are estimated using the EKF. The unmeasured disturbances affecting the process are either modelled as *unstructured noise* affecting all the states or as *structured noise* entering the process predominantly through known, but unmeasured inputs. The first approach is based on direct optimisation of the ML objective function constructed by using the innovation sequence generated from the EKF. The second approach – the extended EM algorithm – is a derivative-free method, that uses the joint likelihood function of the complete data, i.e. states and measurements, to compute the next iterate of the decision variables for the optimisation problem. The efficacy of the proposed approaches is demonstrated on a benchmark continuous fermenter system. The simulation results reveal that both the proposed approaches generate fairly accurate estimates of the noise covariances. Experimental studies on a benchmark laboratory scale heater-mixer setup demonstrate a marked improvement in the predictions of the EKF that uses the covariance estimates obtained from the proposed approaches.

1. Introduction

To operate a chemical process profitably, in a competitive economic environment, it becomes necessary to monitor and tightly control quality variables associated with the process. However, critical quality variables such as product concentrations in reactor/distillation column output streams, molecular weight distribution of a polymer melt or biomass concentration in a fermenter, are difficult to measure on-line. Even when these variables are measured through lab assays, such measurements are infrequent and typically available at irregular intervals. Moreover, even when online measurements of quality variables is feasible, it can prove to be a prohibitively costly option. In such a scenario, dynamic model based estimation of unmeasured states, or a soft sensor, is an attractive alternative for process monitoring and control. With the availability of high speed computers at relatively low costs, process monitoring and advanced multivariable control, which is based on on-line use of mechanistic models, are becoming feasible options in the recent years. Since a mechanistic model is representative of the physical states of the plant, it can be used to deduce information of trajectories of internal unmeasured (or irregularly measured) states at regular and faster rate.

However, even when a reliable mechanistic model for the system under consideration is available, using it for online monitoring and control is not an easy task. Process plants are continuously affected by unmeasured disturbances of different kind and the measurements are corrupted with noise. Thus, it becomes necessary to develop state estimators that systematically fuse noisy measurements with mechanistic models to generate state estimates. The state observers can be developed either through deterministic approaches [1] or through Bayesian approaches [2]. Bayesian approaches provide a systematic approach to handle the unknown inputs affecting the states and the measurement noise. To generate reliable estimates of the unmeasured or infrequently measured states it is important to develop a reasonably accurate characterisation of these unmeasurable signals. This is a critical aspect in the development of Bayesian state estimators. An incorrect choice of noise characteristics leads to deterioration in the performance of the state estimator and, in the worst case, the estimator may diverge [3].

A commonly used assumption in the development of Bayesian state estimation is that the state and measurement disturbances

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