Abstract

In model-based predictive control strategies, accurate estimates of the current state and model parameters are required in order to predict the future system behavior for a given control realization. One particularly powerful approach for constrained nonlinear state estimation is Moving Horizon Estimation (MHE). In MHE past measurements are reconciled with the model response by optimizing states and parameters over a finite past horizon. The basic strategy is to use a moving window of data such that the size of the estimation problem is bounded by looking at only a subset of the available data and summarizing older data in one initial condition term. This also establishes an exponential forgetting of past data which is useful for time-varying dynamics. Compared to other state estimation approaches,MHE offers many advantages following from its formulation as a dynamic optimization problem. Inequality constraints on the variables (states, parameters, disturbances) can be included in a natural way and the nonlinear model equation is directly imposed over the horizon length. Empirical studies show that MHE can outperform other estimation approaches in terms of accuracy and robustness. In addition to these well-known advantages, the framework of MHE allows for formulations different from the traditional (weighted) least-squares formulation.

The greatest impediment to a widespread acceptance of MHE for real-time applications is still its associated computational complexity. Despite tremendous advances in numerical computing and Moore's law, optimization-based estimation algorithms are still primarily applied to slow processes. In this work, we present fast structureexploiting algorithmswhich use robust and efficient numericalmethods andwe demonstrate the increased performance and flexibility of nonlinear constrained MHE.

MHE problems are typically solved by general purpose (sparse) optimization algorithms. Thereby, the symmetry and structure inherent in the problems are not fully exploited. In addition, the arrival cost is typically updated by running a (Extended) Kalman filter recursion in parallel while the final estimate covariance is computed from the derivative information. In this thesis, Riccati based methods are derived which effectively exploit the inherent symmetry and structure and yield the arrival cost update and final estimate covariance as a natural outcome of the solution process.

The primary emphasis is on the robustness of the methods which is achieved by orthogonal transformations. When constraints are imposed, the resulting quadratic programming (QP) problems can be solved by active-set or interior-point methods. We derive modified Riccati recursions for interior-point MHE and show that square-root recursions are recommended in this context because of the numerical conditioning. We develop an activeset method which uses the unconstrained solution obtained from Riccati recursions and employs a Schur complement technique to project onto the reduced space of active constraints. The method involves non-negativity constrained QPs for which a gradient projection method is proposed. We implement the algorithms in efficient C code and demonstrate that MHE is applicable to fast systems.

These QP methods are at the core of solution methods for general convex and nonlinear MHE as is demonstrated. Convex formulations are investigated for robustness to outliers and abrupt parameter changes. Furthermore, the methods are embedded in a Sequential Quadratic Programming strategy for nonlinearMHE.

One application has been of particular interest during this doctoral research: estimation and predictive control of blood-glucose at the Intensive Care Unit (ICU). For this application reliability and robustness of the estimates as well as of the numerical implementations are crucial. We evaluate an MHE based MPC control strategy and show its potential for this application.