Abstract

This thesis discusses nonlinear system identification using kernel based models. Starting from a least squares support vector machine base model, additional structure is integrated to tailor the method for more classes of systems. While the basic formulation naturally only handles nonlinear autoregressive models with exogenous inputs, this text proposes several other model structures. One major goal of this work was to exploit convex formulations or to look for convex approximations in case a convex formulation is not feasible.

Two key enabling techniques used extensively within this thesis are overparametrization and nonquadratic regularization. The former can be utilized to handle nonconvexity due to bilinear products. During this work overparametrization has been applied to handle new model structures. Furthermore it has been integrated with other techniques to handle large data sizes and a new approach to recover a parametrization in terms of the original variables has been derived. The latter technique, nonquadratic regularization, is also suitable to construct convex relaxations for nonconvex problems. In this context the major contribution of this thesis is the derivation of kernel based model representations for problems with nuclear norm as well as group-ℓ_1 norm regularization.

In terms of new or improved model structures, this thesis covers a number of contributions. The first considered model class are partially linear models which combine a parametric model with a nonparametric one. These models achieve a good predictive performance while being able to incorporate physical prior knowledge in terms of the parametric model part. A novel constraint significantly reduces the variability of the parametric model part. The second

part of this thesis, that exploits structure to identify a more specific model class, is the estimation of Wiener-Hammerstein systems. The main contributions in this part are a thorough evaluation on the Wiener-Hammerstein benchmark dataset as well as several improvements and extensions to the existing kernel based identification approach for Hammerstein systems.

Besides targeting more restricted model structures also several extensions of the basic model class are discussed. For systems with multiple outputs a kernel based model has been derived that is able to exploit information from all outputs. Due to the reliance on the nuclear norm, the computational complexity of this model is high which currently limits its application to small scale problems. Another extension of the model class is the consideration of time dependent systems. A method that is capable of determining the times at which a nonlinear system switches its dynamics is proposed. The main feature of this method is that it is purely based on input-output measurements. The final extension of the model class considers linear noise models in combination with a nonlinear model for the system. This work proposes a convex relaxations to estimate the noise model as well as a model capturing the system dynamics by solving a joint convex optimization problem.

The final contribution of this thesis is a reformulation of the classical least squares support vector formulation that allows the analysis of existing models with respect to their sensitivity to perturbations on the inputs.