Identification of Wiener models using Support Vector Regression

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Extended Abstract

In empirical black-box modeling and identification of nonlinear dynamical systems the choice of model structure plays an important role. In model structure selection one needs to take into account the kind of system behaviours which should be described, the effort needed to identify the model parameters from empirical data, and how well the model is suited for its intended use, such as prediction or control. A useful class of nonlinear models consists of block-oriented representations, where various system characteristics, such as nonlinearities and dynamical response, are represented by separate blocks connected in series. Standard nonlinear models of this type are the Wiener and Hammerstein models, where the nonlinearities are captured in a static block and the dynamics are represented by a linear dynamical component.

The Wiener class of models consists of a linear dynamic component followed by a nonlinear static block. In this method the linear dynamic part is expanded in terms of orthonormal basis functions, such as Laguerre and Kautz filters. Support vector regression (SVR) is here applied to determine the nonlinear static block of the Wiener models. In this model structure, the model output is determined as a function of the system input only, and it does not depend on the measured system outputs. Consequently this is an output error identification method. The support vector method is well suited to this kind of system identification problem, as the model can be determined by solving a convex quadratic minimization problem, for which convergence to the global optimum is always obtained. In addition, support vector regression is based on structural risk minimization, which introduces robust performance with respect to new data.

Although Wiener models can approximate any nonlinear system satisfying some mild continuity conditions with any degree of accuracy, they are particularly well suited for modeling processes whose dynamics can naturally be decomposed into a linear dynamical component followed by a static nonlinearity. Typical examples are processes with sensor nonlinearities and pH processes.