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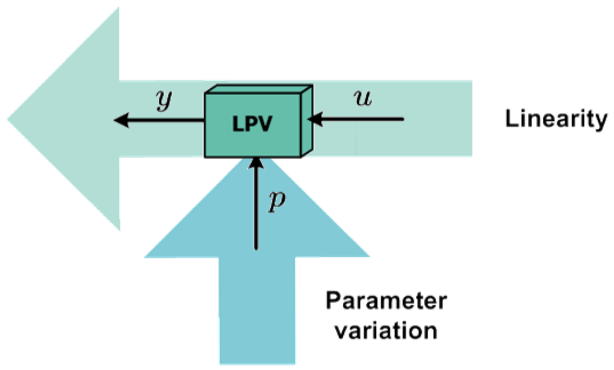
Bayesian Identification of LPV-BJ Models: A Multidimensional Kernel Approach

Mohamed Darwish†, Pepijn Cox†, Gianluigi Pillonetto‡ and Roland Tóth†

† Control Systems Group, Department of Electrical Engineering, Eindhoven University of Technology, The Netherlands, ‡ Information Engineering Department, University of Padova, Italy.

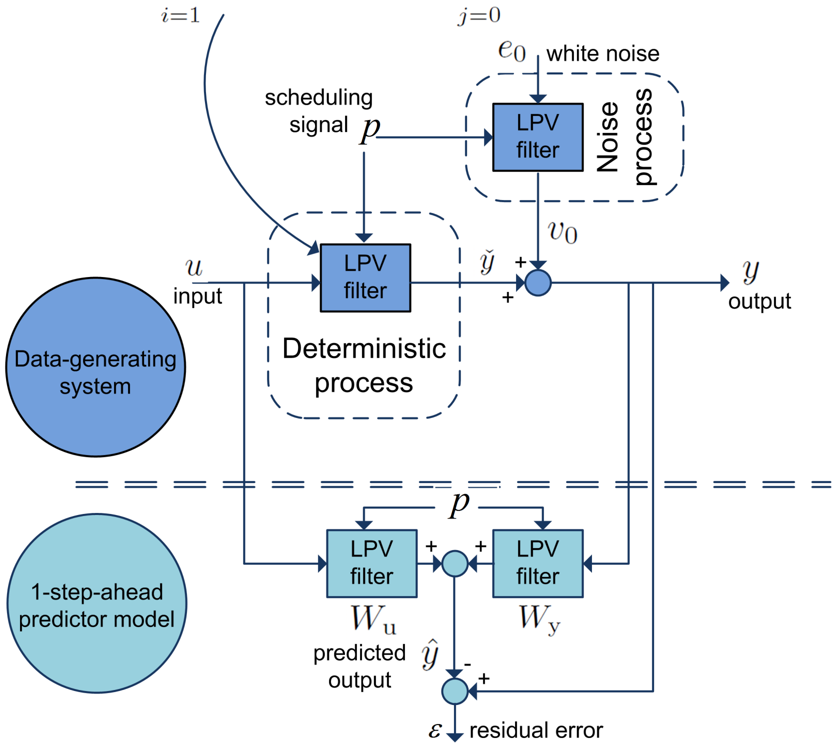
Motivation

Many industrial control systems exhibit nonlinear behaviour, where linear modeling is becoming insufficient to support model based control design such that the increasing performance specifications can be fulfilled. However, *Linear Parameter-Varying* (LPV) systems offer a powerful framework to deal with such situations while preserving the linear relationship between the input and the output signals.



In this work, we introduce a nonparametric approach in a Bayesian setting to efficiently estimate, both in the stochastic and computational sense, LPV Box-Jenkins (LPV-BJ) models.

$$\breve{y}(k) = -\sum_{i=1}^{n_a} a_i(p;k)\breve{y}(k-i) + \sum_{j=0}^{n_b} b_j(p;k)u(k-j)$$



Bayesian identification for LPV-BJ systems

The one-step-ahead predictor (IIRs model form) can be written as

$$y(k) = \underbrace{\underbrace{\sum_{i=1}^{\infty} f_{y_i}(p,k,i)q^{-i}y(k)}_{W_y} + \underbrace{\sum_{j=0}^{\infty} f_{u_j}(p,k,j)q^{-j}u(k)}_{W_u}}_{f=\hat{y}(k|k-1)} + e_0(k), \quad (1)$$

which can be considered as a standard Gaussian process regression model

$$y(k) = f(x^{(k)}) + e_0(k),$$

where $x^{(k)} = \{u^{(k)}, p^{(k)}, y^{(k-1)}\}$ denotes the past measurements till time k, e.g., $u^{(k)} = \{u(\tau)\}_{\tau \le k}$, $f \sim \mathcal{GP}(0, K)$ and it can be viewed as a sum of two independent zero mean Gaussian random fields f^u, f^y

$$f = \sum_{l=1}^{\infty} f_l^y + \sum_{l=1}^{\infty} f_l^u$$

The covariance of f should express

- ➤ coefficient functions dependency on p.
- ➤ Stability of the predictor.

$$K(x^{(k)}, x^{(k')}) = \sum_{l=1}^{\infty} K_l^u(x^{(k)}, x^{(k')}) + \sum_{l=1}^{\infty} K_l^y(x^{(k)}, x^{(k')}),$$

where

$$K_l^y(x^{(k)}, x^{(k')}) = \beta_l^y y(k-l) \exp\left(-\frac{\|p^{(k,l)} - p^{(k',l)}\|_2^2}{\sigma_y^2}\right) y(k'-l),$$

$$K_l^u(x^{(k)}, x^{(k')}) = \beta_l^u u(k-l) \exp\left(-\frac{\|p^{(k,l)} - p^{(k',l)}\|_2^2}{\sigma_u^2}\right) u(k'-l),$$

where $\beta_l^u = \lambda_1 e^{-l\lambda_2}$ and $\beta_l^y = \lambda_3 e^{-l\lambda_4}$ are the so-called decay terms. The hyperparameters are $\sigma_u, \sigma_y, \lambda_1, \lambda_2, \lambda_3, \lambda_4 \in \mathbb{R}^+$. These unknown hyperparameters are tuned using marginal likelihood maximization.

Simulation example

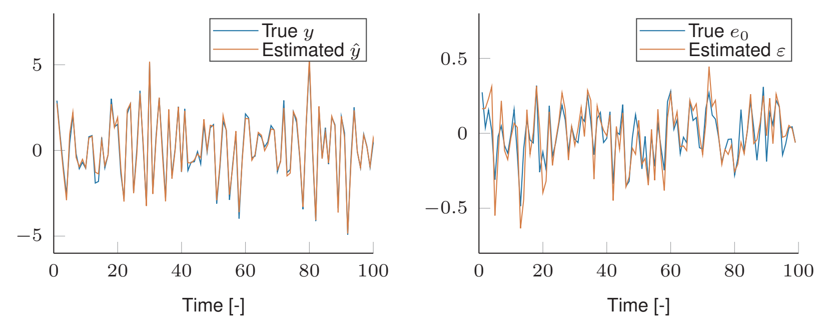
The coefficient functions of the process part of the considered example are

$$\begin{aligned} a_1(\cdot) &= 0.1p^2(k-1), \quad a_2(\cdot) = \tan^{-1}(p(k-1))\cos(p(k-2)), \\ b_0(\cdot) &= -\exp(-p(k)), \quad b_1(\cdot) = 1 - 0.5p^2(k) + p(k-1), \\ b_2(\cdot) &= \tan^{-1}(p(k-2)). \end{aligned}$$

The noise process $v(k)$ is a colored noise generated by an LPV-ARMAX filter with coefficient functions

$$c_1(\cdot) = 0.8p^2(k-1), \quad c_2(\cdot) = 0.5\tan^{-1}(p(k-2)),$$
$$d_1(\cdot) = 0.2p^3(k-1), \quad d_2(\cdot) = 0.5\sin(p(k-2)).$$

The data set consists of 1000 data points with $\mathrm{SNR} = 20\mathrm{dB}$.



(a) System output. (b) Residuals.

Acknowledgments

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