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Data-driven Approximation of Linear Switched Systems

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This contribution addresses the problem of learning dynamical Linear Switched System (LSS) models from input/output observations [1]. The method is illustrated on systems switching between two modes, according to the value of an exogenous signal $p(t) : \mathbb{R}_+ \rightarrow \{0, 1\}$. The LSS G maps its input $u(t)$ to the output $y(t)$, i.e. $y(t) = G[u(t), p(t)]$, see [1] for a rigorous definition.

First, we observe that G can be viewed as a family of linear time-varying (LTV) systems, each corresponding to a fixed switching trajectory. In particular, restricting $p(t)$ to the set of square-wave signals $p_{\omega_0}(t)$ of frequency ω_0 , the collection of periodic LTV systems G_{ω_0} (indexed by ω_0) is defined by $y_{\omega_0}(t) = G_{\omega_0}[u(t)] \triangleq G[u(t), p_{\omega_0}(t)]$. According to Zadeh's theory [3], G_{ω_0} is represented by an ω_0 -periodic transfer function $H_{\omega_0}(j\omega, t)$, that admits a complex Fourier expansion with coefficients $H_{\omega_0}^{(n)}(j\omega)$, $n \in \mathbb{Z}$. Isolating $n = 1$, we define the bivariate function $F(j\omega, j\omega_0) \triangleq H_{\omega_0}^{(1)}(j\omega)$, that is a purely I/O representation, measurable by experiment or simulation in periodic steady-state conditions. Hence, the training dataset is a collection of evaluations $F(j\omega^{(k)}, j\omega_0^{(h)})$.

With this premise, we look for a model \tilde{G} whose associated bi-variate function $\tilde{F}(j\omega, j\omega_0)$ approximates F in a least-squares sense. To this aim, we adopt a Wiener-like model structure [2] for \tilde{G} , whose output is $\tilde{y}(t) = \tilde{G}[u(t), p(t)] = \sum_{i=1}^I \phi_i[p](t) \cdot \psi_i[u](t)$, where $\phi_i[\cdot]$ and $\psi_i[\cdot]$ are LTI systems. Its \tilde{F} -function can be written in pole-residue form as

$$\tilde{F}(j\omega, j\omega_0) = (j\pi)^{-1} \sum_{i,j} r_{ij} (j\omega - \alpha_i)^{-1} (j\omega_0 - \beta_j)^{-1}. \quad (1)$$

We highlight that in the selected model structure, the components $\phi_i[p](t), \psi_i[u](t)$ are the outputs of scalar LTI systems. Model fitting, i.e. optimization of poles α_i, β_j and residues r_{ij} , can be performed using a suitable adaptation of a multivariate rational fitting algorithm. In our experiments, we used the Vector Fitting (VF) algorithm in two steps. First, we view ω_0 as a parameter and run VF to find a set of basis poles α_i to approximate the frequency dependence w.r.t. ω for all sampled values $\omega_0^{(h)}$ collectively. Then, a second run of VF, with fixed α_i , gives poles β_j and residues r_{ij} . Finally, \tilde{G} results from assigning $\phi_i(s) = (s - \alpha_i)^{-1}$, $\psi_i(s) = \sum_j r_{ij} (s - \beta_j)^{-1}$. The input/output stability of the proposed model structure is guaranteed by enforcing strictly negative real part of the estimated poles α_i, β_i using standard techniques. The proposed approach is demonstrated using several benchmark examples of practical interest, including a Buck voltage regulator commonly used to stabilize the microprocessor power supply in electronic systems.

References

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