Combining Experiments for Linear Dynamic Network Identification in the Presence of Nonlinearities

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Combining Experiments for Linear Dynamic Network Identification in the Presence of Nonlinearities

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Abstract. In many practical applications it might be desirable to excite only point at a time in an interconnection of multiple dynamic subsystems (e.g. large-scale system). Therefore multiple experiments need to be combined to successfully identify one or more subsystems in the network of subsystems. This papers illustrates how the identification of a linear subsystem of a dynamical network containing one or more nonlinear subsystems can result in biased estimates when multiple experiments are combined using the Best Linear Approximation (BLA) based approach.

1. Introduction

Large scale mechanical systems consisting of many components, the electrical grid, biological systems or industrial plant can be interpreted as the interconnection of multiple subsystems, i.e. a dynamic network setting.

The identification of linear dynamical networks has received quite some attention over the last years focusing on e.g. network structure detection [1, 2, 3], identification of one or more subsystems in the network [3, 4, 5, 6], input selection [7], and multiple noise frameworks [8, 6]. However, the identification of systems operating in a nonlinear dynamic network has received considerably less attention [9, 10, 11, 12].

In many practical applications it might be desirable to excite only one node at a time in a dynamic network, e.g. for safety reasons, limited actuation capabilities, or due to a geographical spread of the different nodes. Therefore multiple experiments need to be combined to successfully identify of one or more subsystems in the network. This papers illustrates how the identification of a linear subsystem of a dynamical network containing one or more nonlinear subsystems can result in biased estimates when multiple experiments are combined using the Best Linear Approximation (BLA) based approach presented in [12].

A short introduction to nonlinear dynamic networks is given in Section 2. The BLA framework is discussed next in Section 3. Section 4 discusses how multiple experiments can be combined to estimate the subsystems in a dynamic network. A simulation example illustrates that effect of the presence of one or more nonlinearities in the dynamic network on the obtained estimates in Section 5.

2. Dynamic Networks

The dynamic networks considered here follow the same definitions and visualization as in [4, 13]. A dynamic network (see Figure 1) consists of a total of \( L \) nodes, representing internal variables of the network, which are interconnected with other nodes by (nonlinear) dynamic systems. A node signal, denoted \( w_i(t) \), is obtained as the sum of the outputs of the incoming (nonlinear)
Note that in the considered setting, only one reference signal is active simultaneously in each experiment, resulting in a sparse matrix $R(j\omega)$. $W(j\omega)$, unlike $R(j\omega)$, is typically not sparse, since, depending on the interconnections that are present in the network, each reference can evoke a response at each node in the network. In the purely linear case one could also combine the experiments by using the superposition principle.
The nonlinear subsystem $F$ in Figure 5, this reduces the bias on the estimate of module $G$ used to ensure that the nonlinearity is in a similar setpoint for all experiments, as can be observed while $r$.

Case 3: network. Combining these measurements can lead to a bias on the estimates of the linear experiments: each reference signal excites a different range of the nonlinear module of the observed bias can be explained due to the different setpoints of the nonlinearity for the different

Case 2: the proposed framework is tested on a linear dynamic network. As can be expected noise is present in the presented simulation example.

$N = 4096$ points per period. The reference signals have each a standard deviation of 0 amplitude spectrum. The random phases are uniformly distributed between 0 and $2\pi$ all three random phase multisine signals [17] exciting all the frequencies [0, $f$] to the system for each reference signal, each realization contains $P = 2$ steady state periods of $N = 4096$ points per period. The reference signals have each a standard deviation of 0.5. No noise is present in the presented simulation example.

**Case 1:** the proposed framework is tested on a linear dynamic network. As can be expected from [13, 17], an unbiased estimate is obtained, see Figure 3.

**Case 2:** the BLA framework is applied on a nonlinear dynamic network. Figure 4 indicates the clear presence of a bias on the estimate of the linear network module $G_{32}$. The estimate of the network module $G_{31}$ represents the linear approximation of the nonlinear system. The observed bias can be explained due to the different setpoints of the nonlinearity for the different experiments: each reference signal excites a different range of the nonlinear module of the network. Combining these measurements can lead to a bias on the estimates of the linear subsystems connecting to the same node as the nonlinear subsystem, in this case node 3.

**Case 3:** the nonlinear dynamic network is excited by reference signals with different power: while $r_1, r_3$ have a std = 0.5, $r_2$ has a std of 4.5 in this setup. The different reference amplitudes used ensure that the nonlinearity is in a similar setpoint for all experiments, as can be observed in Figure 5, this reduces the bias on the estimate of module $G_{32}$ significantly.

A noiseless estimate of the node signals is obtained: $\hat{W}_{ij}(j\omega) = \sum_{k=1}^{n_k} S_{bla,i,r_k}(q) R_k^{[i]}(j\omega)$. The networked BLA is now obtained in practice as: $\hat{G}_{bla,i}(j\omega) = [K_i^H(j\omega)K_i(j\omega)]^{-1} K_i^H(j\omega)W_i(j\omega)$, where $K_i(j\omega)$, $W_i(j\omega)$, $\hat{G}_{bla,i}(j\omega)$ are given by (the $j\omega$ notation is dropped for compactness):

$$ K_i(j\omega) = \begin{bmatrix} W_i^{[1]} & \cdots & W_i^{[1]} \\ \vdots & \ddots & \vdots \\ W_i^{[M]} & \cdots & W_i^{[M]} \end{bmatrix}, W_i(j\omega) = \begin{bmatrix} W_i^{[1]} \\ \vdots \\ W_i^{[M]} \end{bmatrix}, \hat{G}_{bla,i}(j\omega) = \begin{bmatrix} \hat{G}_{bla,i,1} \\ \vdots \\ \hat{G}_{bla,i,M} \end{bmatrix}. \quad (2) $$

5. Simulation Example

The structure of the simulated system is visualized in Figure 1. The linear subsystems $G_{21}$, $G_{32}$ and $G_{13}$ are first order systems of the form:

$$ x_{ij}(t + 1) = A_{ij}x_{ij}(t) + B_{ij}w_{ij}(t) $$

$$ w_i(t) \quad C_{ij}x_{ij}(t), $$

$$ A_{21} = 0.9, \quad B_{21} = 1.0, \quad C_{21} = 0.5 $$

$$ A_{32} = 0.8, \quad B_{32} = 0.1, \quad C_{32} = 1.0 $$

$$ A_{13} = 0.3, \quad B_{13} = 1.0, \quad C_{13} = -0.9 \quad (3) $$

The nonlinear subsystem $F_{31}$ is given by $w_3(t) = \tanh(w_1(t - 1))$, in the linear simulation case discussed below $F_{31}$ is replaced by a unit delay: $w_3(t) = w_1(t - 1)$.

The system is excited by three reference signals $r_1(t)$, $r_2(t)$ and $r_3(t)$. These signals are all three random phase multisine signals [17] exciting all the frequencies $|0, f_s/2|$ with a flat amplitude spectrum. The random phases are uniformly distributed between 0 and $2\pi$. Only one reference signal is active simultaneously. $M = 20$ realizations of the multisines are applied to the system for each reference signal, each realization contains $P = 2$ steady state periods of $N = 4096$ points per period. The reference signals have each a standard deviation of 0.5. No noise is present in the presented simulation example.
6. Conclusion

While combining experiments for the estimation of dynamic modules in linear dynamic networks still leads to consistent estimates using the BLA-framework, a bias can be introduced on the BLA-framework estimates in case one or more of the network modules behaves nonlinear. This nonlinearity is caused by combining measurements where the nonlinearity operates in a different setpoint, leading to different approximations of this nonlinear behavior.

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