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Optimal identification experiment design for the interconnection of locally controlled systems ☆

Xavier Bombois [a,*], Anton Korniienko [a], Håkan Hjalmarsson [b], Gérard Scorletti [a]

[a] Laboratoire Ampère, Ecole Centrale de Lyon, 36 avenue Guy de Collongue, 69134 Ecully Cedex, France
[b] Automatic Control, School of Electrical Engineering, KTH, 100 44, Stockholm, Sweden

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ABSTRACT

This paper considers the identification of the modules of a network of locally controlled systems (multi-agent systems). Its main contribution is to determine the least perturbing identification experiment that will nevertheless lead to sufficiently accurate models of each module for the global performance of the network to be improved by a redesign of the decentralized controllers. Another contribution is to determine the experimental conditions under which sufficiently informative data (i.e. data leading to a consistent estimate) can be collected for the identification of any module in such a network.

1. Introduction

In this paper, we consider the problem of designing an identification experiment that will allow to improve the global performance of a network made up of the interconnection of locally controlled systems. The identification experiment will be designed in such a way that we obtain a sufficiently accurate model of each module in the network to be able to improve the global performance of the network by redesigning the local controllers. The type of networks considered in this paper is usual in the literature on multi-agent systems (see e.g. Fax and Murray, 2004; Korniienko, Scorletti, Colinet, and Blanco, 2014).

This paper contributes to the efforts of developing techniques for the identification of large-scale or interconnected systems when the topology of the network is known. In many papers, the problem is seen as a multivariable identification problem and structural properties of the system are then used to simplify this complex problem (see e.g. Haber and Verhaegen, 2013). The identifiability of the multivariable structure is studied in a prediction error context in Weerts, Dankers, and Van den Hof (2015) while this multivariable structure is exploited in other papers to reduce the variance of a given module in the network (see Everitt, Bottegal, Rojas, and Hjalmarsson, 2015; Gunes, Dankers, and Van den Hof, 2014; Hägg and Wahlberg, 2014). Unlike most of these papers, we consider here a network whose interconnection is realized by exchanging the measured (and thus noisy) output of neighboring modules. Another important difference is that, in our setting, all modules can be identified independently using single-input single-output identification. Consequently, we are close to the situation considered in our preceding papers on dynamic network identification (see e.g. Dankers, Van den Hof, Bombois, and Heuberger, 2016). In these contributions, we have developed conditions for consistent estimation of one given module in a dynamic network. Since general networks were considered in these contributions, the data informativity was tackled with a classical condition on the positivity of the spectral density matrix (Ljung, 1999). The first contribution of this paper is to extend these results for the considered type of networks by giving specific conditions for data informativity. In particular, we show that it is not necessary to excite a specific module i to consistently identify it as long as there exists at least one path from another module j to that particular module i. In this case, the noise present in the noisy output measurement y_j will give sufficient excitation for consistent estimation.

However, the main contribution of this paper is to tackle the problem of optimal experiment design for (decentralized) control in a network context. More precisely, our contribution lies in the design of the identification experiment that will lead to sufficiently accurate models of each module of the network to guarantee a certain level of global performance via the design of local controllers. The identification experiment consists of simultaneously applying an excitation signal in each module (i.e. in each closed-loop system) and our objective is to design the spectra of each

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* Corresponding author.
E-mail addresses: xavier.bombois@ec-lyon.fr (X. Bombois), anton.korniienko@ec-lyon.fr (A. Korniienko), hakan.hjalmarsson@ee.kth.se (H. Hjalmarsson), gerard.scorletti@ec-lyon.fr (G. Scorletti).

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of these excitations signals in such a way that the global control objective is achieved with the least total injected power. In this sense, we extend the results in Barenthin, Bombois, Hjalmarsson, and Scorletti (2008) and Bombois, Scorletti, Gevers, Van den Hof, and Hildebrand (2006) considering one local loop with a local performance objective to the case of network of closed-loop systems with (both a local and) a global performance objectives. Like in Barenthin et al. (2008) and Bombois et al. (2006), the uncertainty of an identified model will be represented via its covariance matrix. The difference is that this covariance matrix will here be a function of the excitation signals injected in each module that has a path to the considered module and of course that there will be a covariance matrix per identified module. Like in Barenthin et al. (2008) and Bombois et al. (2006), the maximal allowed uncertainty will be determined using tools from robustness analysis. To avoid heavy computational loads linked to a high number of modules N_{mod} and to structured uncertainties characterized by N_{mod} uncertain parameter vectors, the uncertainty is first projected into an unstructured uncertainty on the complementary sensitivity describing each connected closed-loop system and then the robustness analysis is based on the interconnection of these unstructured uncertainties. This approach (called hierarchical approach) to analyze the robustness of large-scale (interconnected) systems has been introduced in Safonov (1983) and further developed in Dinh, Korniienko, and Scorletti (2014). A technical contribution of this paper is to develop a methodology that allows the use of the hierarchical approach in the presence of the nonstandard uncertainty delivered by system identification. The methodology developed in this paper allows to perform the robustness analysis via the hierarchical approach in an efficient way. It is nevertheless to be noted that, as was also observed in Barenthin et al. (2008), the corresponding optimal experiment design problem cannot be convexified and has thus to be tackled via a (suboptimal) iterative approach inspired by the so-called D–K iterations (Zhou & Doyle, 1998).

Note also that the framework considered here is much different than the frameworks of Hägg and Wahlberg (2015) and Vincent, Novara, Hsu, and Poolla (2010) which is, to our knowledge, the only other papers treating the optimal experiment design problem in a network. In Vincent et al. (2010), the authors consider input design for nonparametric identification of static nonlinearities embedded in a network. The main purpose of Hägg and Wahlberg (2015) lies in the use of measurable disturbances in optimal experiment design.

Notations. The matrix

$$\begin{pmatrix} X_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & X_N \end{pmatrix}$$

will be denoted $diag(X_1, \ldots, X_N)$ if the elements X_i ($i = 1, \ldots, N$) are scalar quantities while it will be denoted $bdiag(X_1, \ldots, X_N)$ if the elements X_i ($i = 1, \ldots, N$) are vectors or matrices.

2. Identification of interconnected systems

2.1. Description of the network configuration

We consider a network made up of N_{mod} single-input single-output (SISO) systems $\mathcal{S}_i$ ($i = 1 \ldots N_{mod}$) operated in closed loop with a SISO decentralized controller K_i ($i = 1 \ldots N_{mod}$):

$$\mathcal{S}_i : \; y_i(t) = G_i(z, \theta_{i,0}) u_i(t) + v_i(t) \tag{1}$$

$$u_i(t) = K_i(z)(y_{ref,i} - y_i(t)) \tag{2}$$

$$\bar{y}_{ref}(t) = \mathcal{A}\, \bar{y}(t) \; + \; \mathcal{B}\, ref_{ext}(t). \tag{3}$$

Let us describe these equations in details. The signal u_i is the input applied to the system $\mathcal{S}_i$ and y_i is the measured output. This output is made up of a contribution of the input u_i and of a disturbance term $v_i(t) = H_i(z, \theta_{i,0}) e_i(t)$ that represents both process and measurement noises. The different systems $\mathcal{S}_i$ ($i = 1 \ldots N_{mod}$) are thus described by two stable transfer functions $G_i(z, \theta_{i,0})$ and $H_i(z, \theta_{i,0})$, the later being also minimum-phase and monic. The signals e_i ($i = 1 \ldots N_{mod}$) defining v_i are all white noise signals. Moreover, the vector $\bar{e} \stackrel{\Delta}{=} (e_1, e_2, \ldots, e_{N_{mod}})^T$ has the following property:

$$\begin{aligned} E\bar{e}(t)\bar{e}^T(t) &= \Lambda \\ E\bar{e}(t)\bar{e}^T(t-\tau) &= 0 \;\text{ for } \tau \neq 0 \end{aligned} \tag{4}$$

with E the expectation operator and with Λ a strictly positive definite matrix. With (4), the power spectrum $\Phi_{\bar{e}}(\omega)$ of $\bar{e}$ is given by $\Phi_{\bar{e}}(\omega) = \Lambda$ for all ω. We will further assume that the signals e_i ($i = 1 \ldots N_{mod}$) are mutually independent. The matrix Λ is then diagonal[1] i.e. $\Lambda = diag(\Lambda_{1,1}, \Lambda_{2,2}, \ldots, \Lambda_{N_{mod},N_{mod}}) > 0$.

The systems $\mathcal{S}_i$ in (1) may all represent the same type of systems (e.g. drones). However, due to industrial dispersion, the unknown parameter vectors $\theta_{i,0} \in \mathbf{R}^{n_{\theta_i}}$ can of course be different for each i, as well as the order of the transfer functions G_i and H_i. Consequently, it will be necessary to identify a model for each of the systems $\mathcal{S}_i$ in the sequel.

In this paper, we consider the type of interconnections used in formation control or multi-agent systems (see e.g. Fax and Murray, 2004; Korniienko et al., 2014). As shown in (2), each system $\mathcal{S}_i$ is operated with a decentralized controller $K_i(z)$. In (2), the signal $y_{ref,i}$ is a reference signal that will be computed via (3). The matrix $\mathcal{A}$ and the vector $\mathcal{B}$ in (3) represent the interconnection (flow of information) in the network and we have $\bar{y}_{ref} = (y_{ref,1}, y_{ref,2}, \ldots, y_{ref,N_{mod}})^T$ and $\bar{y} = (y_1, y_2, \ldots, y_{N_{mod}})^T$. The signal ref_{ext} is a (scalar) external reference signal that should be followed by all outputs y_i and that is generally only available at one node of the network.

As an example, let us consider the network in Fig. 1. In this network, we have $N_{mod} = 6$ systems/modules, all of the form (1) and all operated as in (2) with a decentralized controller K_i. These local closed loops are represented by a circle/node in Fig. 1 and are further detailed in Fig. 2 (consider $r_i = 0$ for the moment in this figure). The objective of this network is that the outputs y_i of all modules follow the external reference ref_{ext} even though this reference is only available at Node 1. For this purpose, a number of nodes are allowed to exchange information (i.e. their measured output) with some other neighboring nodes. The arrows between the nodes in Fig. 1 indicate the flow of information. For example, Node 5 receives the output of two nodes (i.e. Nodes 3 and 4) and sends its output (i.e. y_5) to three nodes (Nodes 3, 4 and 6). The reference signal $y_{ref,i}$ of Node i will be computed as a linear combination of the received information at Node i. For Node 5, $y_{ref,5}$ will thus be a linear combination of y_3 and y_4. More precisely, for all outputs y_i to be able to follow the external reference ref_{ext}, $\mathcal{A}$ and $\mathcal{B}$ in (3) are chosen as (Fax & Murray, 2004; Korniienko et al., 2014):

$$\mathcal{A} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 1/3 & 0 & 1/3 & 1/3 & 0 & 0 \\ 0 & 0.5 & 0 & 0 & 0.5 & 0 \\ 0 & 0.5 & 0 & 0 & 0.5 & 0 \\ 0 & 0 & 0.5 & 0.5 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \quad \mathcal{B} = (1, 0, \ldots, 0)^T.$$

[1] We will nevertheless see in the sequel that many of the results of this paper also apply to the case of spatially-correlated noises e_i i.e. to the case where (4) holds with a matrix $\Lambda = \Lambda^T > 0$ that is not necessarily diagonal.