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Research article

Detection of no-model input-output pairs in closed-loop systems

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ABSTRACT

The detection of no-model input-output (IO) pairs is important because it can speed up the multivariable system identification process, since all the pairs with null transfer functions are previously discarded and it can also improve the identified model quality, thus improving the performance of model based controllers. In the available literature, the methods focus just on the open-loop case, since in this case there is not the effect of the controller forcing the main diagonal in the transfer matrix to one and all the other terms to zero. In this paper, a modification of a previous method able to detect no-model IO pairs in open-loop systems is presented, but adapted to perform this duty in closed-loop systems. Tests are performed by using the traditional methods and the proposed one to show its effectiveness.

1. Introduction

In a survey conducted by Honeywell in refineries, chemical, petrochemical and pulp and paper plants, out of the 11,000 control loops analyzed, 97% of them use the PID algorithm [7]. However, the search for reduction of losses, for increased efficiency and for the use of more complex systems led many industries to adopt new control algorithms. These algorithms typically rely on a well-designed model.

A non-trivial part of any control system is the process of modeling. System Identification is an approach that uses algorithms to obtain mathematical models, representing dynamic systems. The result of the identification is a model, that represents the relationship between the inputs and outputs of a system. The System Identification process goes through the following steps: experimental design, data collection, selection of candidates for the structure of the model and definition of model parameters, model estimation and validation. Thus, the design of plant tests to generate data for identifying dynamic models is critically important to develop model-based process control systems.

In order to improve the design of the identification experiments, a pre-identification step is usually applied. It is a previous step to identification, which aims to acquire process information to improve the experiment design. The purpose of this step is to provide previous information regarding static gain of the process, system order and time delay estimation. Usually, a simple signal such as a pulse or square wave is applied individually to each input.

Generally, issues related to IO selection are part of the Control Structure Design stage, after the plant model has already been identified. In this context, IO selection is described as the procedure of selecting suitable variables u to be manipulated by the controller (plant inputs) and suitable variables y to be supplied to the controller (plant outputs). This approach can lead to model-plant mismatch and poor controller performance, because models can be identified for decoupled IO pairs (no-model IO pairs). On the other hand, our approach detects no-model IO pairs in a preliminary stage of the identification process. The objective is the detection of no-model IO pairs in a pre-identification stage, to improve the effectiveness of the excitation signals in the identification experiment and to increase the efficiency of the identification algorithms. An extensive survey of methods for IO selection can be found in Van der Wal and de Jager [19].

In MIMO systems, the models can be represented by transfer matrices. When an output is not affected by the action of an entry, the transfer function of this pair is zero and therefore it is said that there is a zero in the transfer matrix in this position.

Frequently, it is necessary to identify the plant in closed-loop, because it may be risky to open the control loops. In this sense, the objective of this paper is to improve and to adapt the Fuzzy Input-Output Detection (FIOD) method applicable to open-loop systems, published by Potts et al. [14] to detect no-model IO pairs in closed-loop MIMO systems.

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2. No-model IO selection methods

Several papers in the literature address the issue of the no-model IO combination. The most common methods are based on the controllability of the model. Methods based on controllability of inputs and outputs seek to determine which candidate sets of inputs and outputs will be eliminated or kept, based on a quantitative measure of this controllability. In this sense, several methods apply the concept of controllability of inputs and outputs, based on the singular value decomposition.

The methods based on the minimum singular value select candidate sets of inputs and outputs that maximize the smallest singular value in defined frequencies. Some methods that implement or support this approach were proposed in Refs. [13,17,8,15], among others. Similarly, other methods choose the maximum singular value to transform a matrix into its simplest possible form, which is diagonal.

Although these methods present good reliability when used in open-loop systems, they normally fail when used in the detection of no-model IO combinations in closed-loop MIMO systems, because of the controller action. A properly designed and tuned controller will lead the direct steady-state gains (main diagonal) close to unity and inverted diagonal steady-state gains of the transfer matrix close to zero (decoupling). Thus, inverted diagonal IO combinations will have their closed-loop steady-state gains approximately equal to zero and equal to each other, regardless of being or not related (having a model or not).

2.1. Covariance and correlation analysis in closed-loop systems

The limitation of the methods based on correlation analysis applied to detect no-model IO pairs in closed-loop MIMO systems was first discussed in Box [3]. Afterwards, Vaillant et al. [18] discussed the use of correlation analysis methods for closed-loop and showed how the control action distorts the determination of no-model IO pair detection in closed-loop.

Next, a new approach to detect no-model IO pairs in closed-loop MIMO systems is proposed. The analysis is based on covariance and the correlation between the signals of the system. This approach is a modification of the FIOD method proposed in Ref. [14] for open-loop systems.

Fig. 1 shows a single closed-loop control of a multivariable process. The signals and blocks presented in this figure are: setpoint $r_j(t)$, error signal $\epsilon_j(t)$, controller $C_{ij}(q)$, controller output $u_j(t)$, nominal model of the plant $G_{ij}(q)$, disturbance of the process $e_i(t)$, process output $y_i(t)$ and disturbance model $H_i(q)$, with $i = 1, \ldots, n$ and with $j = 1, \ldots, m$, where m represents the number of inputs and n the number of outputs.

Typically, the correlation analysis is carried out between the process input (u_j) and the process output (y_i), but due to the limitations cited before, a new approach is suggested. Our analysis consists of computing the covariance and the correlation between the setpoint (r_j) and the process output (y_i), not between (u_j) and (y_i) as is commonly done. Classical methods of IO pair detection fail in closed-loop systems if only the relationship between process variables (outputs) and input signals (setpoints) are analyzed. However, in our analysis, the setpoint signals (r_j) and the controller outputs (u_j) are used.

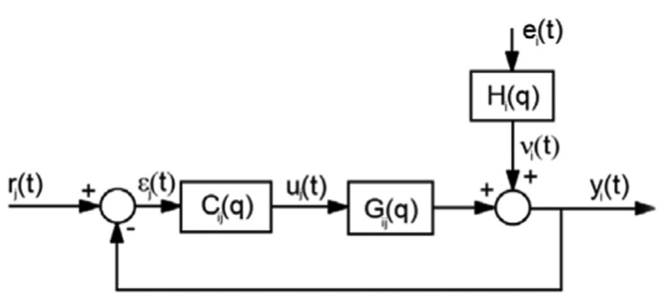

Fig. 1. Diagram of the closed-loop system.

Consider firstly an open-loop system represented by the following equation:

$$y_i(t) = \sum_{k=1}^{\infty} g_{i,j}(k)q^{-k}u_j(t) + \sum_{k=0}^{\infty} h_i(k)q^{-k}e_i(t) \tag{1}$$

If Eq. (1) is multiplied by $u_j(t+\tau)$, we have:

$$y_i(t)u_j(t+\tau) = \sum_{k=1}^{\infty} g_{ij}(k)q^{-k}u_j(t)u_j(t+\tau) + \sum_{k=0}^{\infty} h_i(k)q^{-k}e_i(t)u_j(t+\tau) \tag{2}$$

Next, we assume that expectation E refers to the stochastic components of signal $\chi(t)$ and symbol $\bar{\mathrm{E}}$ is defined by (3) as in Ljung [9]:

$$\bar{\mathrm{E}}\left[\chi(t)\right] = \lim_{N\to\infty}\frac{1}{N}\sum_{t=1}^{N}\mathrm{E}\left[\chi(t)\right] \tag{3}$$

Then, by applying the expectation operator $\bar{\mathrm{E}}$ in (2),

$$\bar{\mathrm{E}}\left[y_i(t)u_j(t+\tau)\right] = \sum_{k=1}^{\infty} g_{i,j}(k)q^{-k}\bar{\mathrm{E}}\left[u_j(t)u_j(t+\tau)\right] + \sum_{k=0}^{\infty} h_i(k)q^{-k}\bar{\mathrm{E}}\left[e_i(t)u_j(t+\tau)\right] \tag{4}$$

If the input is subject to a quasi-stationary sequence with:

$$\bar{\mathrm{E}}\left[u_j(t)u_j(t-\tau)\right] = R_{u_j}(\tau) \tag{5}$$

and

$$\bar{\mathrm{E}}\left[e_i(t)u_j(t-\tau)\right] \equiv 0 \tag{6}$$

where (6) is valid only for open-loop systems, then in accordance with Theorem 2.2 of Ljung [9],

$$\bar{\mathrm{E}}\left[y_i(t)u_j(t-\tau)\right] = R_{y_iu_j}(\tau) = \sum_{k=1}^{\infty} g_{ij}(k)q^{-k}R_{u_j}(k-\tau). \tag{7}$$

It can be demonstrated that if the input is not white noise, it is possible to estimate the covariance $(\hat{R}_u^N)$ and the cross-covariance functions $(\hat{R}_{yu}^N)$ as:

$$\hat{R}_{u_j}^N(\tau) = \frac{1}{N}\sum_{t=\tau}^{N} u_j(t)u_j(t-\tau) \tag{8}$$

and

$$\hat{R}_{y_iu_j}^N(\tau) = \sum_{k=1}^{M} \hat{g}_{ij}(k)q^{-k}\hat{R}_{u_j}^N(k-\tau) \tag{9}$$

and by solving (9) it is possible to estimate the vector $\hat{g}_{ij}(k)q^{-k}$.

Consider again the closed-loop system described by (4). In system identification, due to the manner in which the tests are performed, the signals usually have zero mean. In such cases, autocorrelation and cross-correlation functions match the auto-covariance and cross-covariance functions [1]. The correlation coefficient is proportional to the cross-covariance function between two variables. Therefore, it can be concluded that the vector is proportional to the correlation coefficient.

Following the same approach used in the open-loop case, the next result is obtained:

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