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Model Predictive Control oriented experiment design for system identification: A graph theoretical approach

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ABSTRACT

We present a new approach to Model Predictive Control (MPC) oriented experiment design for the identification of systems operating in closed-loop. The method considers the design of an experiment by minimizing the experimental cost, subject to probabilistic bounds on the input and output signals due to physical limitations of actuators, and quality constraints on the identified model. The excitation is done by intentionally adding a disturbance to the loop. We then design the external excitation to achieve the minimum experimental effort while we are also taking care of the tracking performance of MPC. The stability of the closed-loop system is guaranteed by employing robust MPC during the experiment. The problem is then defined as an optimization problem. However, the aforementioned constraints result in a non-convex optimization which is relaxed by using results from graph theory. The proposed technique is evaluated through a numerical example showing that it is an attractive alternative for closed-loop experiment design.

1. Introduction

1.1. Motivations and objectives

MPC has become very important for controlling constrained multivariable processes in industry. As in any other model-based controller, the MPC performance highly depends on the quality of the model being used. However, modeling and identification are known to be very demanding in terms of time and resources. On the other hand, due to unavoidable changes in the dynamics of the process over time, for example because of raw material variations or equipment wear, the model has to be updated regularly. Therefore, there is an emerging demand for more efficient data driven modeling and model updating techniques [26].

A primary step in any modeling approach based on experimental data is to monitor the behaviour of the system and collect data. The collected data can highly affect the efficiency of the system identification. This concept has led to the growth of the topic of experiment design for system identification, see [11]. Identification experiments can be done in either open or closed-loop conditions. However, in many practical applications, systems can only operate under closed-loop settings due to stability issues, production restrictions, economic considerations or inherent feedback mechanisms which necessitate designing and performing system identification experiments under closed-loop settings. A well known problem in closed-loop identification is the conflict between the identification and control requirements, i.e., while more exciting inputs can increase the quality of the identified model, the control performance will be affected by the presence of exciting inputs.

The closed-loop experiment design problem can be translated into the design of an additive external excitation. The existing literature on closed-loop experiment design for linear systems is quite rich, see [13,14,16,17] and the references therein. However, many of these methods have difficulty in dealing with nonlinear and implicit feedback such as MPC. In [7] a graph theoretical approach is explored, but a known controller is assumed and indirect identification is employed.

1.2. Related work

The existing literature on closed-loop experiment design for MPC is quite rich. A large portion of the literature trying to find a balance between the identification and control requirements in the MPC by adding a new constraint to the MPC optimization problem, which can assure persistent excitation of the controlled input signal, see for example [1,8,18,23]. In [12], an approach to online

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experiment design for MPC is proposed, which is based on certainty equivalence. This method also requires integrating new constraints to MPC. However, the main difference with previous approaches is that the proposed method by Heirung et al. [12] tries to reduce the parameter uncertainties at the same time. More research related to experiment design for MPC can be found in [28,29].

There are a few challenges in the implementation of the existing methods: (a) the obtained optimization problem that needs to be solved at each iteration of MPC is nonconvex; (b) in the presence of process and measurement noises the input and output constraints which arise for safety or practical limitations should be imposed probabilistically and this cannot be handled by the existing methods.

1.3. Statement of contributions

In this paper, which is an extension of the idea developed by Ebadat et al. [7] to more general controllers with implicit control law, we present a new approach for MPC oriented experiment design in the presence of probabilistic constraints on input and output signals.

The idea is to design the external excitation achieving the minimum experimental effort, while we are also taking care of the tracking performance of MPC. We add a constraint on the quality of the estimated model in terms of the Fisher information matrix [11]. The objective is to obtain an exciting enough input signal guaranteeing that the estimated model is in the set of models that satisfy the desired control specifications with a given probability, i.e., we follow the idea of application oriented input design, see [3,9,15]. Furthermore, it is important to find a trade-off between the identification and control objectives. In this work the control objective is considered in the cost function and the identification requirement is imposed by adding a constraint on the minimum information that should be extracted from the closed-loop system.

Adding an external excitation can improve the information content of the closed-loop system, however, since the system is operating in closed-loop using nominal MPC may not guarantee stability of the closed-loop system under external excitations. In other words, there exists a contradiction between the control and identification objectives. This problem has been addressed in [10] by generalizing the punctual stability concept to set stability. One contribution of the current paper is that we address this issue by interpreting the external excitation as a bounded disturbance. We thus employ robust output feedback MPC which can assure the stability of the system under bounded input disturbances [25]. This can be considered as one of the extensions of this work compared to [7] where the stability of the closed-loop system is assumed to be guaranteed and not investigated.

On the other hand, the resulting optimization program arising from the input design formulation is non-convex. A convex approximation of the problem can be found by extending the results in [33], where the problem is defined as finding the optimal probability density function (pdf) for the external excitation instead. The probability distribution of the external excitation is then characterized as the convex combination of the measures describing the set of n-dimensional distributions of stationary Markov processes of a given order. The resulting problem is convex in the decision variables.

Moreover, the above mentioned optimization problem requires to know the control law in order to evaluate and predict the cost and constraints for different external excitations. For online controllers such as MPC the control law is not known in advance and instead it is an implicit and nonlinear function of the observed state. Thus, the proposed method in [7] cannot be employed in its current form. This difficulty is also handled by evaluating MPC for each of measures defining the convex hull of the set of n-dimensional distributions of stationary Markov processes of a given order. Thus, a set of offline evaluations of the closed-loop system is required. However, since the controller is model-based the evaluations cannot be performed on the real plant and instead a simulated model is used.

1.4. Structure of the manuscript

This paper is organized as follows: In Section 2 the problem is defined and the existing challenges are described. Section 3 discusses the application of a graph theoretical approach in finding the convex approximation and solving the problem. Section 4 contains some numerical results and evaluates the effectiveness of the proposed approach.

Notation: $\mathbb{R}$ stands for the real set and $\mathbb{R}^{n\times m}$ is the set of real $n\times m$ matrices. The expected value and the probability measure associated with a given random variable are denoted by $\mathbb{E}\{\cdot\}$, and $\mathbb{P}\{\cdot\}$ respectively. Sometimes a subscript is added to $\mathbb{E}$ and $\mathbb{P}$ to clarify the random variables involved.

2. Problem definition

The problem considered in this paper is the following. Assume that the goal is to identify a linear, discrete and time invariant system, which is described in state space form as

$$\mathcal{S}: \begin{cases} x_{t+1} = A_0 x_t + B_0 u_t, \\ y_t = C_0 x_t + \nu_t, \end{cases} \tag{1}$$

As a first step to identify a model for (1), we define a model class $\mathcal{M}$, which is parametrized by the vector $\theta \in \mathbb{R}^{n_\theta}$ such that the system $\mathcal{S}$ is identifiable [20].The model set considered here is given by

$$\mathcal{M}(\theta): \begin{cases} x_{t+1} = A(\theta)x_t + B(\theta)u_t, \\ y_t = C(\theta)x_t + \nu_t, \end{cases} \tag{2}$$

where $\{\nu_t\}$ is the white measurement noise introduced in (1). It is assumed that the model (2) coincides with system (1) when $\theta=\theta_o$, i.e., there is no undermodeling [20]. We call θ_o the true parameter vector.

The system $\mathcal{S}$ in (1) is operating in closed-loop with a controller designed based on the best available estimation of θ_o (denoted by $\hat{\theta}$) such that the closed-loop system is having acceptable performance. The closed-loop setting is shown in Fig. 1, where y_t^d is the reference signal. In the following, we assume that the system $\mathcal{S}$ in (1) is being controlled by MPC, and the resulting closed-loop system is asymptotically stable.

Due to changes in the process dynamics over time, at some point the plant-model mismatch increases such that the closed-loop performance is not satisfactory. In order to detect the performance deterioration, the degradation in the control performance that comes from the mismatch between the model and the system is quantified with the definition of an application cost-function, which is a scalar measure of the performance deterioration. We denote such a cost by $V_{\text{app}}(\theta)$. By employing the application

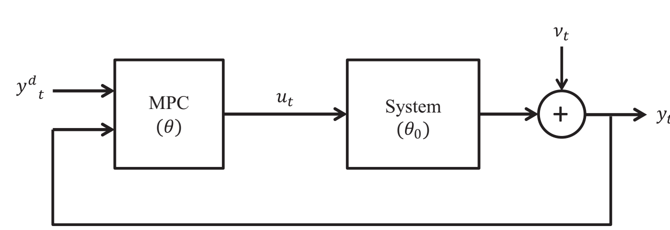

Fig. 1. Block diagram of the closed-loop system.