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An application-oriented approach to dual control with excitation for closed-loop identification

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ABSTRACT

Identification of systems operating in closed loop is an important problem in industrial applications, where model-based control is used to an increasing extent. For model-based controllers, plant changes over time eventually result in a mismatch between the dynamics of any initial model in the controller and the actual plant dynamics. When the mismatch becomes too large, control performance suffers and it becomes necessary to re-identify the plant to restore performance. Often the available data are not informative enough when the identification is performed in closed loop and extra excitation needs to be injected. This paper considers the problem of generating such excitation with the least possible disruption to the normal operations of the plant. The methods explicitly take time domain constraints into account. The formulation leads to optimal control problems which are in general very difficult optimization problems. Computationally tractable solutions based on Markov decision processes and model predictive control are presented. The performance of the suggested algorithms is illustrated in two simulation examples comparing the novel methods and algorithms available in the literature.

1. Introduction

Most modern control design approaches are model based. For example, in process industry, model predictive control (MPC) has more or less become the industry standard for control of constrained MIMO systems. Any control system has performance requirements and whenever controllers are model based, the quality of the model influences the achievable performance. This means that the implementation of model-based controllers often requires significant modeling efforts for the control to be successful. This modeling is often done using system identification and a lot of time and resources are spent on the initial, commissioning identification. However, even if the initial model gives satisfactory control, changes in the process dynamics over time can result in reduced performance and the need for re-identification to restore performance.

It is well-known that identification in closed loop can cause problems due to lack of excitation in the input. The reason for this is that often the regulating properties that one desires from the controller are in conflict with the excitation properties of the signals needed for identification. The compromise between these properties has lead to the study of dual control introduced by Feldbaum [13]. This has been recognized in the MPC community and several MPC formulations where a dual effect is included in the input have appeared in the literature. One of the earliest seems to have been proposed by Genceli and Nikolaou [15]. Similar ideas have later been proposed by Aggelogiannaki and Sarimveis [2], Marafioti [41] and Rathouský and Havlena [47]. They all propose amending the MPC with a constraint that renders the input persistently exciting over some horizon. This ensures that the closed-loop data can be used to estimate models consistently.

The choice of the input signal used in the identification is a very important one. A badly designed input signal could potentially ruin the (in other aspects) most well-prepared identification experiment. Conversely, a carefully chosen input signal could reduce the experimental effort needed to get a certain accuracy of the identified model and simplify the system identification problem per se. This understanding has led to the growth of the branch of input or experiment design in system identification.

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Early contributions were thanks to, for example, Fedorov [12], Mehra [43] and Goodwin and Payne [19]. Later ideas, where the intended model use is taken into account, have been developed by Gevers and Ljung [18], Hjalmarsson et al. [26] and Bombois et al. [8], to name a few.

This paper considers the problem of optimal experiment design for system identification of constrained systems operating in closed loop. The central idea is that the quality of the identified model should be high enough to give good performance when the model is used in a controller. It is also desirable that the cost of the system identification experiment is as low as possible. The cost of an experiment depends on the application but can, for example, be specified in terms of disruption of normal operations, or the time of the experiment.

The goal of the paper is to present the optimal experiment design problem and the theoretical and practical challenges that this problem entails. The paper also presents suitable approximations that can be made to arrive at computationally tractable and practically implementable formulations. The problem is initially formulated as a general optimal control problem. This problem has a nice solution for linear systems without time domain signal constraints, but is computationally intractable in general. Using the framework of constrained Markov decision processes, the problem is then formulated for systems with finite state and action spaces. Although this formulation is very general, the size of the resulting optimization problem makes it computationally demanding and practical applicability is limited. Therefore, the problem is further simplified using a receding horizon formulation. This has been a successful strategy to approximate optimal control problems with constraints in many applications. For completeness, existing receding horizon formulations are also presented. In going from the most general formulation, through a series of simplifying assumptions and approximations, the challenges of the optimal experiment design problem are highlighted.

The presented ideas and algorithms explicitly take the intended model use into account by using ideas from the *application-oriented input design* framework [25], which in turn is part of the least costly identification paradigm [8]. These frameworks typically result in less disruption from normal operations compared to imposing persistence of excitation.

1.1. Organization of the paper

The remaining paper is organized as follows. Section 2 presents the necessary mathematical background. In Section 3, the general control formulation with excitation for closed loop re-identification is introduced. Section 4 presents an MDP formulation of the problem in a general setting. In Section 5, two MPC based controllers for systems of output error type are introduced. Section 6 discusses some of the related, earlier approaches based on the idea of adding persistence of excitation to the input. Section 7 illustrates the performance of the algorithms in simulations. Finally, Section 8 concludes the paper and points to some future research directions.

1.2. Notation

The symbol $\mathbb{P}\{\cdot\}$ denotes the probability of an event and $\mathbb{E}\{\cdot\}$ denotes the expectation operator for the probability spaces generated by the relevant stochastic processes. The real numbers are denoted $\mathbf{R}$. Matrices are capital letters, e.g. X, Y, and vectors are small letters, e.g. x, y. For symmetric matrices, $X \succcurlyeq 0$ means that X is positive semidefinite and for two symmetric matrices X and Y, $X \succcurlyeq Y$ means $X - Y \succcurlyeq 0$. For a vector x and matrix Q, the notation $\|x\|_Q \triangleq \sqrt{x^T Q x}$ is used.

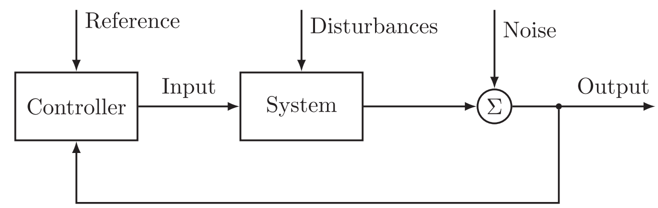

Fig. 1. A general closed loop system. The system is driven by the input and disturbance processes and the controller chooses the input based on feedback measurements and reference signals. Typically, the feedback is corrupted by measurement noise.

2. Preliminaries

This paper deals with methods for input design for closed-loop system identification. The system, model and input design theory and assumptions used in the development of the methods are introduced here. The general closed-loop setup is shown in Fig. 1.

2.1. System and model

Consider a linear, time invariant, discrete time multiple-input, multiple-output systems modeled by

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

where $x_t \in \mathbf{R}^n$ is the state, $u_t \in \mathbf{R}^m$ is the input, $v_t \in \mathbf{R}^p$ represents the effects of disturbances and noise and is a zero mean white sequence with covariance Λ_v, and $y_t \in \mathbf{R}^p$ is the measured output. This model class is known as innovations' models and covers, e.g., ARMAX and Box-Jenkins transfer function models [35]. The model is parameterized by the unknown vector $\theta \in \mathbf{R}^{n_\theta}$. It is assumed that there exists a vector θ_o such that the true system $\mathcal{S}$ is given by $\mathcal{S} = \mathcal{M}(\theta_o)$.

The state and output of the system $\mathcal{S}$ can be predicted using the standard Kalman filter, given by

$$\begin{cases} \hat{x}_{t+1|t} = A(\theta_o)\hat{x}_{t|t-1} + B(\theta_o)u_t + K(\theta_o)(y_t - C(\theta_o)\hat{x}_{t|t-1}), \\ \hat{y}_{t|t-1} = C(\theta_o)\hat{x}_{t|t-1}. \end{cases} \tag{2}$$

It is well-known that for Gaussian noise, this estimate is the mean square optimal predictor. For the general case, the Kalman filter gives the linear least squares estimate (see [49, for example]).

2.2. Controller

The input to the system, u_t, is generated by the controller. The controller decides on the choice of the input at a given time instant, u_t, according to a control rule, denoted π_t. A sequence of such control rules is called a *policy* and is denoted $\pi = (\pi_1, \pi_2, \ldots)$.

There is an instantaneous cost, $c_t(x, u)$, related to the system being in a state x and using a certain control u. Based on the instantaneous costs c_t, the expected average costs can be defined, for a finite control horizon T as

$$C^\pi = \frac{1}{T}\sum_{t=1}^{T} \mathbb{E}^\pi\{c_t(x_t, u_t)\}, \tag{3}$$