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A multi-iteration pseudo-linear regression method and an adaptive disturbance model for MPC

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ABSTRACT

This paper proposes an MPC method that uses an adaptive disturbance model to improve the accuracy of prediction. In unmeasured disturbance model identification, a novel multi-iteration pseudo-linear regression (MIPLR) method is used which is more accurate and has faster convergence than traditional recursive identification methods. The adaptive disturbance model is used in an MPC scheme for improved performance in disturbance rejection. The method is demonstrated by the simulation of a distillation column and also tested on the real process. The test results show that the proposed MPC scheme can not only increase control performance, but also increase robustness.

1. Introduction

Model predictive control (MPC) refers to a class of control algorithms that optimize plant behavior over a finite-time horizon based on an explicit mathematical model. MPC has been applied widely in controlling multiple-input multiple-output (MIMO) processes with constraints. Finite impulse response (FIR) and step response models are adopted in primal MPC formulations such as dynamic matrix control (DMC) [1] and the quadratic DMC (QDMC) [2]. They have had an enormous impact on industrial process control and served to define the industrial MPC paradigm [3]. Clarke and colleagues [4] proposed the generalized predictive control (GPC) in which transfer functions are used. In recent years, MPC in state space form has been an area of intensive research [5] and has also been employed in industrial MPC techniques, e.g., SMOC by Shell and SSC by AspenTech [3].

MPC is a model-based technique. Therefore model accuracy plays an important role in the performance of MPC systems. Modeling error and unmeasured disturbances can lead to poor control performance. The constant state disturbance model is a standard technique in linear quadratic regulator design [6]. In DMC and QDMC, a constant output step disturbance model is used to achieve offset-free control. This method has proved to be simple to implement and robust in real practice. However, it is less effective in rejecting unmeasured disturbances which are not steps. To improve the rejection of input disturbances, a ramp model to represent the output disturbance was suggested by Morari and Lee [7]. These methods work well under the special assumption of a ramp model on the disturbance. Wellons and Edgar [8] presented a generalized analytical predictor by using a first-order or second-order transfer function to estimate the effect of disturbance. However, fixed disturbance models have limited performance when disturbance properties are time varying. Shen and Lee [9] proposed an adaptive inferential control to identify an AR model for the disturbances in real time. In order to achieve a better performance, Karra and co-workers [10] proposed an adaptive MPC scheme in which the process model and disturbance model are updated on-line by two separate recursive pseudo-linear regression schemes. The input-output data is used to identify an output error (OE) model to describe process model, while the residuals generated by the OE model are modeled by ARMA processes. This approach has practical problems: when there are no test signals applied, there is a persistent excitation problem for process model identification; when test signals are used, the process is continuously disturbed. Gerksic, Strmcnik and van den Boom [11] presented a tuning procedure for the Kalman filter, based on the sensitivity functions, in order to improve the sluggish rejection of disturbances. Although robustness is considered, it is difficult to maintain the performance as disturbances in industrial processes are diverse and time varying. Muske and Badgwell [12] proposed

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a disturbance model that adds step disturbances either to the state or to the process outputs for linear MPC in state space framework. Moreover corresponding conditions are derived for guaranteeing zero steady-state offset. A general disturbance model for systems in which the controlled variables and measured ones are distinct is proposed by Pannocchia and Rawlings [13]. The difference between [12] and [13] is that [12] uses a block-diagonal structure for the disturbance model; while [13] use and unstructured model.

In industrial MPC applications for continuous process units working at stationary operating points, we have observed that the process dynamics from inputs to outputs do not change for a long period of time; but the character of unmeasured disturbances change frequently. For example, in the refining/petrochemical industry, unmeasured disturbances are caused by variations in feed composition, in weather conditions, and in steam pressure. These variations cannot be modeled as stationary stochastic processes. In this work, we will develop an MPC technique that uses a fixed process model and an on-line identified adaptive disturbance model. The process model is identified by some identification methods, say, the asymptotic method (ASYM) [14,26], using externally excited input–output data. The unmeasured disturbances at the outputs are modeled as a time varying process filtered by an integrated white noise sequence [15]; a time series ARMA model is used to describe the dynamics of the disturbances. Traditional adaptive MPC, in which both process model and disturbance models are adapted, may suffer from poor excitation conditions if no test signals are applied; whereas in the proposed method no persistent excitation problem will occur as long as the simulation errors are non zeros. The proposed method is also much simpler than traditional adaptive MPC.

The idea can be used in any MPC algorithms. Due to its popularity, the DMC structure is used to illustrate the concept proposed in this paper. Like the representation given by Lundstrom, Lee, Morari and Skogestad [16], in this paper, the DMC algorithm is separated into two parts, a predictor and an optimizer; and the modification is made in the predictor part. The model prediction of MPC is improved without influencing the optimizer.

In recursive (adaptive) disturbance model identification a multi-iteration pseudo-linear regression (MIPLR) method is proposed in order to obtain accurate and fast converging model parameters.

The outline of the paper is as follows: in Section 2, the basis of DMC algorithm is reviewed briefly; Section 3 presents the proposed method; in Section 4, the recursive identification method is developed and a simulation is used to show its performance. An industrial case study from a chemical plant is carried out in Section 5; Section 6 contains the conclusion and discussion.

2. Dynamic matrix control (DMC)

In the DMC algorithm, a step response model of the plant is used to predict the future behavior of the controlled variables, and a quadratic performance objective over a finite prediction horizon is adopted to compute optimal control moves.

2.1. Plant model representation

Assume that there is a MIMO plant with n_y outputs and n_u inputs. Denote $y(t)$ as the output vector at time t and $u(t)$ as the input vector at time t. The ith output is described by

$$y_i(t) = \sum_{j=1}^{n_u}\sum_{k=1}^{\infty} s_{i,j,k}\Delta u_j(t-k), \quad (1 \le i \le n_y) \tag{1}$$

where $s_{i\ j\ k}$ denotes the kth element of step response, $\Delta u_j(t) = u_j(t) - u_j(t-1)$.

The step response sequence of the ith output to the jth input is

$$[s_{i,j,1}, \ldots, s_{i,j,n}, s_{i,j,n+1}, \ldots], \quad (1 \le i \le n_y, 1 \le j \le n_u) \tag{2}$$

For a stable plant this sequence will asymptotically reach a constant value, i.e., $s_{i,\ j,\ n+m} \approx s_{i,\ j,\ n}$, $(m > 0)$.

Thus, the plant outputs over n future time steps can be expressed in the following state space form [17]:

$$\begin{aligned} \mathbf{Y}(t+1) &= \mathbf{M}\mathbf{Y}(t) + \mathbf{S}\Delta\mathbf{u}(t) \\ \mathbf{y}(t) &= \mathbf{N}\mathbf{Y}(t) \end{aligned} \tag{3}$$

where

$$\begin{aligned} &\mathbf{Y}(t) = [\mathbf{y}^{\mathrm{T}}(t|t-1), \mathbf{y}^{\mathrm{T}}(t+1|t-1), \ldots, \mathbf{y}^{\mathrm{T}}(t+n-1|t-1)]^{\mathrm{T}} \\ &\mathbf{y}^{\mathrm{T}}(t+k|t-1) = [y_1(t+k|t-1), y_2(t+k|t-1), \ldots, \\ &y_{n_y}(t+k|t-1)], \quad k = 0, \ldots, n-1 \\ &\Delta\mathbf{u}^{\mathrm{T}}(t) = [\Delta u_1(t), \Delta u_2(t), \ldots, \Delta u_{n_u}(t)] \end{aligned}$$

$$\mathbf{M} = \begin{bmatrix} 0 & \mathbf{I}_{n_y} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{I}_{n_y} & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I}_{n_y} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{I}_{n_y} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{I}_{n_y} \end{bmatrix}, \quad \mathbf{N} = \underbrace{[\mathbf{I}_{n_y}, \mathbf{0}, \cdots, \mathbf{0}]}_{n \cdot n_y},$$

$$\mathbf{S} = \begin{bmatrix} \mathbf{S}_1 \\ \mathbf{S}_2 \\ \vdots \\ \mathbf{S}_{n-1} \\ \mathbf{S}_n \end{bmatrix}, \quad \mathbf{S}_t = \begin{bmatrix} s_{1,1,t} & s_{1,2,t} & \cdots & s_{1,n_u,t} \\ s_{2,1,t} & s_{2,2,t} & \cdots & s_{2,n_u,t} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n_y,1,t} & s_{n_y,2,t} & \cdots & s_{n_y,n_u,t} \end{bmatrix}, \quad t = 1, \ldots, n.$$

$\Delta\mathbf{u}(t)$ is a vector of changes in the manipulated inputs at time t. $\mathbf{y}(t)$ is the output vector at time t. The vector $\mathbf{Y}(t)$ represents the dynamic states of the system. Each element, $\mathbf{y}(t+k|t-1)$,has a special physical interpretation: it is the future output vector at time $t+k$ assuming the input remain constant starting at time $t-1$ [i.e., $\Delta\mathbf{u}(t+j) = 0$ for $j \geqslant 0$]. The new state vector $\mathbf{Y}(t+1)$ is the old vector $\mathbf{Y}(t)$ shifted up n_y elements plus the contribution made by the latest input change $\Delta\mathbf{u}(t)$.

2.2. DMC predictor and offset-free strategy

A constant output step disturbance model is adopted by DMC to achieve offset-free control for step-like disturbances. At time t, based on model (3), the past control moves and the measured output, the predicted outputs are computed by [16]:

$$\begin{aligned} \widehat{\mathbf{Y}}(t|t-1) &= \mathbf{M}\widehat{\mathbf{Y}}(t-1|t-1) + \mathbf{S}\Delta\mathbf{u}(t-1) \\ \hat{\mathbf{y}}(t|t-1) &= \mathbf{N}\widehat{\mathbf{Y}}(t|t-1) \\ \widehat{\mathbf{Y}}(t|t) &= \widehat{\mathbf{Y}}(t|t-1) + \xi_{\mathrm{DMC}}(\tilde{\mathbf{y}}(t) - \hat{\mathbf{y}}(t|t-1)) \end{aligned} \tag{4}$$

where $\widehat{\mathbf{Y}}(t|t-1)$ denotes the estimate of $\mathbf{Y}(t)$ based on the measurements up to time $t-1$, $\widehat{\mathbf{Y}}(t|t)$ is the corrected estimate of $\mathbf{Y}(t)$ based on the measurements up to time t, $\hat{\mathbf{y}}(t|t-1)$ is the prediction of output at time t based on the measurements up to time $t-1$, $y(t)$ is the measured output at time t.

In DMC predictor (4),

$$\xi_{\mathrm{DMC}} = \underbrace{[\mathbf{I}_{n_y}, \quad \mathbf{I}_{n_y}, \ldots, \mathbf{I}_{n_y}]}_{n \cdot n_y} \tag{5}$$

The correction in Eq. (5) is equivalent to assuming an output disturbance that remains constant for all future time. This method is simple and applied widely in industrial model predictive control. In this work we will develop more sophisticated disturbance model in order to improve the prediction accuracy and hence control performance.