1994023393 N94-27896

ON IDENTIFIED PREDICTIVE CONTROL

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1. INTRODUCTION

Self-tuning control algorithms are potential successors to manually tuned PID controllers traditionally used in process control applications. A very attractive design method for self-tuning controllers, which has been developed over recent years, is the long-range predictive control (LRPC). The success of LRPC is due to its effectiveness with plants of unknown order and dead-time which may be simultaneously nonminimum phase and unstable or have multiple lightly damped poles (as in the case of flexible structures or flexible robot arms).

LRPC is a receding horizon strategy and can be, in general terms, summarized as follows. Using assumed long-range (or multi-step) cost function the optimal control law is found in terms of: (1) unknown parameters of the predictor model of the process, (2) current input-output sequence, (3) future reference signal sequence. The common approach is to assume that the input-output process model is known or separately identified and then to find parameters of the predictor model. Once these are known, the optimal control law determines control signal at the current time t which is applied at the process input and the whole procedure is repeated at the next time instant.

Most of the recent research in this field is apparently centered around the LRPC formulation developed by Clarke *et al.* [1, 2], known as Generalized Predictive Control (GPC). GPC uses ARIMAX/CARIMA model of the process in its input-output formulation. An excellent presentation of predictive controller design in a unified fashion is given by Soeterboek [5] and an interesting application is presented by Soeterboek et al. [6].

In this paper, the GPC formulation is used but the process predictor model is derived from the state space formulation of the ARIMAX model and is directly identified over the receding horizon, i.e., using current input-output sequence. The underlying technique in the design of Identified Predictive Control (IPC) algorithm is the identification algorithm of observer/Kalman filter Markov parameters developed by Juang *et al.* [3] at NASA Langley Research Center and successfully applied to identification of flexible structures.

2. MODEL OF THE PROCESS

Consider the following locally linearized input-output model of a process under sampled-data control :

$$y(t) = [A(q^{-1})\Delta]^{-1} B(q^{-1}) \Delta u(t) + v(t) \qquad (1)$$

with

$$v(t) = [A(q^{-1})\Delta]^{-1} \xi(t) \qquad (2)$$

where the process input $u(t) \in R^r$, the process output $y(t) \in R^m$, $\xi(t)$ is white noise with variance σ^2, and $A(q^{-1})$ and $B(q^{-1})$ are polynomial matrices in unit delay operator q^{-1}, and $\Delta = \Delta(q^{-1}) = 1 - q^{-1}$. The same model can be found by representing the standard state space model with output noise as

$$x(t) = Ax(t) + B\Delta^{-1}(\Delta u(t))$$
$$y(t) = Cx(t) + v(t) \tag{3}$$

or

$$x(t) = \underline{A}x(t) + \underline{B}\Delta u(t) \tag{4a}$$
$$y(t) = \underline{C}x(t) + v(t) \tag{4b}$$

Thus, the ARIMAX/CARIMA model is represented in state space by a model with output noise and incremental control input and is the starting point in this research.

3. PREDICTIVE CONTROL ALGORITHM

In its standard formulation, predictive control algorithm is based on the following minimum variance j-step-ahead predictor $\hat{y}(t+j)$ of the process output $y(t)$ given by equations (1) and (2):

$$\begin{aligned}\hat{y}(t+j) &= G_0\Delta u(t+j-1) + G_1\Delta u(t+j-2) + \ldots + G_{j-1}\Delta u(t) \\ &+ \overline{G}_j(q^{-1})\Delta u(t-1) + F_j(q^{-1})y(t) \\ &\overset{df}{=} \tilde{G}_j(q^{-1})\Delta u(t+j-1) + \overline{G}_j(q^{-1})\Delta u(t-1) + F_j(q^{-1})y(t)\end{aligned} \tag{5}$$

where $\tilde{G}_j(q^{-1})$, $\overline{G}_j(q^{-1})$ and $F_j(q^{-1})$ are polynomial matrices. In this equation, $\hat{y}(t+j)$ is expressed as a function of future incremental control inputs, past incremental control inputs and present and past outputs.

The control sequence $\tilde{u}$ is determined as one minimizing a quadratic cost function given as

$$J(k) = \sum_{j=N_s}^{N} e^T(t+j)e(t+j) + \lambda \sum_{j=1}^{NU} \Delta u^T(t+j-1)\Delta u(t+j-1) \tag{6}$$

where

λ	is the nonnegative weighting factor identical for all inputs for simplicity,
N_s	is the starting horizon of prediction,
NU	is the control horizon identical for all inputs for simplicity,
$e(t+j)$	is the predicted system error defined by

$$e(k+j) \overset{df}{=} w(k+j) - \hat{y}(k+j) \tag{7}$$

with $\{w(k+j); j = 1,2,\ldots\}$ being the future reference vector sequence.

Defining $\tilde{u}^T \overset{df}{=} [\Delta u^T(t) \quad \Delta u^T(t+1) \quad \ldots \quad \Delta u^T(t+N-1)]$, the solution for $J_{\min}$ giving the optimal control is

$$\tilde{u} = (\underline{G}^T G + \lambda I)^{-1}\underline{G}^T(w - F) \tag{8}$$

where

$$\underline{G} = \begin{bmatrix} G_{N_s} & \cdots & G_1 & G_0 & & & \\ G_{N_s+1} & \cdots & \cdots & G_1 & G_0 & & \\ \vdots & & & & \ddots & \ddots & \\ & & & & & \ddots & G_0 \\ & & & & & & G_1 \\ \vdots & & & & & & \vdots \\ G_N & \cdots & & & & \cdots & G_{NU} \end{bmatrix}_{(N-N_s+1)\times NU} \tag{9}$$

and F represents predicted system response due to the past input-output sequence. Since $\Delta u(t)$ is the first element of $\tilde{u}$, the control signal $u(t)$ applied at the plant input is

$$u(t) = u(t-1) + \bar{g}(w - F) \tag{10}$$

where $\bar{g}$ is the first raw of $(\underline{G}^T \underline{G} + \lambda I)^{-1} \underline{G}^T$.

4. MAIN CONTRIBUTION: IDENTIFIED PREDICTIVE CONTROL (IPC)

In this research, using the ARIMAX state space model (4) of the MIMO process, the j-step-ahead predictor $\hat{y}(t+j)$ of the process output is identified directly, without prior identification of any other model of the process. The j-step-ahead predictor, defined by equation (5), consists of two parts: $\tilde{G}_j(q^{-1})\Delta u(t+j-1)$ is due to the future or predicted control signals and two remaining terms in (5) being due to the past input-output sequence. In our approach, parameters involved in the determination of both parts are obtained directly using input-output data sequence.

The IPC control law is constantly corrected for any changes in process parameters through extracting the relevant information from the current input-output sequence. Since IPC uses properly defined observer model of the j-step-ahead predictor, its identification has dead beat properties that makes IPC particularly suitable for control plants with lightly damped modes such as flexible structures.

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