Engineering Applications of Artificial Intelligence 67 (2018) 331–344

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Particle swarm optimization based fuzzy gain scheduled subspace predictive control

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A R T I C L E I N F O

Keywords:
Subspace predictive control
Fuzzy gain scheduling
Particle swarm optimization
Optimal automatic tuning

A B S T R A C T

The key feature of data-driven Subspace Predictive Control (SPC) is its capability in on-line and automatically adaptation of SPC gains with no need to obtain the explicit model of the system. This feature makes SPC suitable to control nonlinear and time-varying systems. However, in conventional SPC persistently excitation (PE) signals are required to update the SPC gains in the presence of system variations. This procedure demands high computational load and has convergency issues. In this paper we propose a new approach to eliminate the requirement of applying PE signals without degrading the SPC performance. This can be done by using Particle Swarm Optimization (PSO) based Fuzzy Gain Scheduling (FGS) method to optimally update the SPC gains directly with no need to apply PE signals. The method is denoted by PSO-based FGS-SPC. In PSO-based FGS-SPC the SPC gains are optimally adapted by utilizing and evaluating auxiliary scheduling variables, which are correlated with the changes in system dynamics, as soon as a changes are observed in system dynamics without applying PE signals. Eliminating the PE in our proposed method reduces the computational load drastically. Moreover, in PSO-based FGS-SPC, the controller gain ranges (CGRs) of FGS technique are optimally auto-tuned by minimizing the SPC cost function via the PSO algorithm. As a result, the difficulty in finding the CGRs in FGS procedure for inverting the normalized gains is overcome by applying PSO technique on FGS. Consequently, the PSO-based FGS-SPC shows more efficient controlling performance than the SPC by optimally adapting the SPC gains. In addition, PSO-based FGS-SPC shows fast convergence capability and time efficiency over the SPC. Simulation results confirm efficiency and robustness of the method in the presence of constraints and noisy data.

1. Introduction

In last three decades Predictive Controllers became most widely used advanced controllers in the process control in industry (Qin and Badgwell, 2003; Lee, 2011). In general, predictive control is a control strategy which obtains the control signal by using a predictive model of the process in a cost function minimization. The procedure is done over a fixed prediction horizon in the presence of constraints. There are two different approaches for predictive control: *model-based* approach and *data-driven* approach. Model-based approach is called Model Predictive Control (MPC) (Lee, 2011; Wang, 2009). Process model is the basic requirement of the design in MPC. Then the predictor matrices are obtained from the process model, and the controller is designed by using the predictor matrices. Therefore, in MPC the closed-loop performance of the system heavily depends on the accuracy of the process model, which is utilized to design the predictor. Since most industrial systems are nonlinear and time-varying, modeling is considered as the most challenging and time consuming work in MPC design, which demands to apply advanced and sophisticated modeling methods with any variations in the system (Liu and Chan, 2006; Liu et al., 2010; Kong et al., 2016). On the other hand, data-driven approach is constructed based on combination of Subspace Identification Methods (SIM) (Katayama, 2005; Overschee and De Moor, 1996) and predictive control, which is called Subspace Predictive Control (SPC) (Favoreel and De Moor, 1999; Kadali et al., 2003). In SPC the predictor matrices are determined directly from I/O data with no need to obtain the parametric model of the process, and the predictor is called *Subspace Predictor.* Main advantage of SPC is its capability to adapt the SPC gains on-line by applying persistency excitation (PE) signals, collecting new I/O data and updating the subspace predictor matrices in data-driven manner. This feature makes SPC much more appropriate than MPC to control time-varying and nonlinear systems. SPC has also other features, which has made it one of the popular control strategies in

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https://doi.org/10.1016/j.engappai.2017.10.009
Received 6 February 2017; Received in revised form 26 September 2017; Accepted 2 October 2017
0952-1976/

industrial applications over the past decade (Kadali et al., 2003; Mardi and Wang, 2009) such as, chemical engineering (Jing et al., 2015), vehicle control (Lu et al., 2015), smart grids and buildings (Shafiei et al., 2015), network control systems (Wang et al., 2017). These features are: (i) No prior knowledge is needed on the order and model structure of the system, (ii) Same cost function and same tuning parameters as MPC, but no need to solve the Diophantine equation, (iii) Is based on the reliable and numerically robust linear algebra tools such as Singular value decomposition (SVD) and QR decomposition, (iv) No need for iterative algorithms to obtain predictor matrices, (v) Easily applicable to multi-variable systems.

The main requirement to collect sufficient information from new I/O data and to predict the system outputs accurately is that the input signals have to be persistently exciting the system. These PE signals are applied to the system whenever the thresholding error is flacked. However, because of the high computational load and disruption in system operation, the all-times persistent excitation should be avoided, especially in the steady-state mode. Therefore, much attention is given to replacing this disruptive and time consuming updating process with an efficient algorithm (Zacokova et al., 2013). Although, there have been some attempts to reduce the destructive effects of applying the all-time PE signals, but none of them could completely eliminate the requirement of persistent excitation in SPC and applying PE signals is still open problem in SPC. There are several works that proposed algorithms to address the persistently excitation issues. For instance, in Aggelogiannaki and Sarimveis (2006) the excitation method is illustrated by formulating additional constraints to the optimization problem, however, this approach results in solving non-convex optimization problem to compute the control signal at each time step. A similar approach is also found in Marafioti et al. (2014) to assure PE in the input signal. In Navalkar et al. (2014) the issue of persistency of excitation is addressed in subspace predictive repetitive control and requirement of applying PE signals is relaxed and limited by using basis functions for identification. On the other hand, Hallouzi and Verhaegen (2008) adds an extra term to the cost function to ensure the PE and keeps the optimization problem convex and quadratic, however, it degraded the control performance. A recursive SPC technique based on the Givens rotations and variable forgetting factors is demonstrated in Mardi and Wang (2009), which considers a posteriori prediction error based strategy to determine the sufficient time to apply the PE signal to the system, but it cannot completely eliminate the side effect of applying PE signals and PE still disrupts the system operation in steady-state mode.

A commonly used scheme in industry to deal with the issue of dynamic behavior changes in time-varying systems is applying a *Gain Scheduling* (GS) technique (Astrom and Wittenmark, 1994). In GS technique the controller parameters are updated by monitoring different operating conditions of the process. GS technique was first introduced in about 1950 s with application on flight control systems (Astrom and Wittenmark, 1994), and it is very useful technique to reduce the effects of parameter variation in different processes, such as pH control, fuel-air control in car engine and ship steering (Astrom and Wittenmark, 1994). Since the parameter updating procedure is done based on open-loop or pre-programmed way, it is controversial to consider the GS technique as an *adaptive* system. However, by utilizing and evaluating some auxiliary scheduling variables, which are correlated with the changes in system dynamics the GS technique can be considered as an adaptive controller (Astrom and Wittenmark, 1994). In this case there is no need to estimate and identify the system parameters, because the controller parameters can be updated quickly by using the auxiliary scheduling variable values, as soon as a changes are observed in the system dynamics. The main issue in design of GS system is finding suitable auxiliary scheduling variables, which is done in model-based approach in GS technique. On the other hand, there is a fuzzy logic based approach to GS technique which can overcome this disadvantage of conventional GS technique. The approach is called *Fuzzy Gain-Scheduling* (FGS) technique. There are many successful implementation of FGS in the literature to control nonlinear and time-varying systems (Chiu et al., 2005; Kakigano et al., 2013; Sarma, 2001; Yang et al., 2014), and FGS-PID, which is one of the most popular FGS techniques in industry (Bedoud et al., 2015; Huang and Yu, 2001; Kanthaphayao and Chunkag, 2014; Rodriguez-Martinez et al., 2011; Santos and Dexter, 2002).

In Sedghizadeh and Beheshti (2016) we have proposed a new FGS-SPC method by applying the FGS algorithm for on-line updating of the SPC controller gains using a fuzzy-logic-based GS method. In proposed FGS-SPC algorithm in Sedghizadeh and Beheshti (2016), tracking error, variation of past output data and variation of past control signal are considered as the auxiliary scheduling variables of FGS procedure. Therefore, the SPC gains are updated by evaluating these auxiliary scheduling variables with no need to apply aforementioned disruptive PE signals. This feature makes the FGS-SPC method much more reliable and time efficient than the conventional SPC method. Moreover, FGS-SPC technique enables SPC controller users to apply any advanced model-free gain-scheduling algorithms such as, auto-tuning adaptive methods (Poulin et al., 1996), self-tuning fuzzy-logic based techniques (Altas, 1997; Muhammad et al., 2013; Visioli, 2001) and fuzzy neural networks (Shen, 2001) to re-tune the SPC gains. FGS is a well-known technique in industry with various successful applications to control of nonlinear and time-varying systems (Bedoud et al., 2015; Chiu et al., 2005; Huang and Yu, 2001; Kakigano et al., 2013; Kanthaphayao and Chunkag, 2014; Rodriguez-Martinez et al., 2011; Sarma, 2001; Yang et al., 2014). However, implementing the FGS-SPC method has two issues. First, FGS-SPC is a suboptimal solution, which cannot include the SPC cost function minimization in the algorithm (Sedghizadeh and Beheshti, 2016). Second, there is a well-known issue in FGS implementation, which is the choice of controller gain ranges (CGRs), Huang and Yu (2001), Zhao et al. (1993). Currently, these CGRs are calculated in an ad hoc manner by the designer, which is a complex procedure especially for time-varying and nonlinear systems. The issue was addressed in the literature, and several methods were presented to determine the CGRs in FGS of PID controller (Chaiyatham and Ngamroo, 2014; Huang and Yu, 2001; Woo et al., 2000; Zhao et al., 1993; Bouallegue et al., 2012). For example, in Zhao et al. (1993) CGRs are determined in FGS-PID by rule of thumb based on extensive simulation studies and by using the gain and period of oscillation at the stability limit under proportional control. The CGRs are replaced by proper adjustment rates in Huang and Yu (2001) to generate the degrees of gain difference. However, the rates still need to be selected by the user according to the several simulation results of FGS-PID. In Woo et al. (2000) the CGRs are considered as scaling factors for a PID-type fuzzy controller, and a self-tuning method is presented to tune them based on tracking-error-based functions. However, the simulation results show a considerable overshoot at the transient response of the controlled system. An optimal FGS-PID control is also presented in Chaiyatham and Ngamroo (2014) to enhance the performance of conventional PID controller. The method uses bee colony optimization technique to automatically tuning the scaling factors, membership functions and control rules of the FGS-PID controller automatically. However, on-line tuning of all membership functions and control rules is a complex task and demands high computational load. In Bouallegue et al. (2012) a Particle Swarm Optimization-based (PSO-based) strategy is provided for tuning the scaling factors in a PID-type fuzzy logic controller, by considering a cost function to minimize the maximum overshoot and the integral of absolute error. The approach is compared with standard Genetic Algorithm (GA) approach which shows computational efficiency and converges superiority of the PSO-based algorithm.

In this paper, we equip the FGS-SPC method with PSO technique to overcome the existing CGRs tuning problem of FGS and simultaneously optimizing the SPC cost function. The proposed method is denoted by PSO-based FGS-SPC. This method updates the SPC gains with no need to apply PE signals. Consequently, the PSO-based FGS-SPC can update both the SPC controller gains and the CGRs of FGS optimally by using the