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A self-tuning fuzzy controller for a class of multi-input multi-output nonlinear systems

Chengying Xu [a], Yung C. Shin [b,*]

[a] Department of Mechanical, Materials & Aerospace Engineering, University of Central Florida, Orlando, FL 32816, USA
[b] School of Mechanical Engineering, Purdue University, West Lafayette, IN 47907, USA

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ABSTRACT

This paper presents a systematic design procedure of a multivariable fuzzy controller for a general Multi-Input Multi-Output (MIMO) nonlinear system with an input–output monotonic relationship or a piecewise monotonic relationship for each input–output pair. Firstly, the system is modeled as a Fuzzy Basis Function Network (FBFN) and its Relative Gain Array (RGA) is calculated based on the obtained fuzzy model. The proposed multivariable fuzzy controller is constructed with two orthogonal fuzzy control engines. The horizontal fuzzy control engine for each system input–output pair has a hierarchical structure to update the control parameters online and compensate for unknown system variations. The perpendicular fuzzy control engine is designed based on the system RGA to eliminate the multivariable interaction effect. The resultant closed-loop fuzzy control system is proved to be passive stable as long as the augmented open-loop system is input–output passive. Two sets of simulation examples demonstrate that the proposed fuzzy control strategy can be a promising way in controlling multivariable nonlinear systems with unknown system uncertainties and time-varying parameters.

1. Introduction

Many complex industrial systems are multivariable and nonlinear. When developing a multivariable fuzzy controller for these systems, it is often difficult to infer a proper command for each control variable due to the high dimension of requisite control rule matrices and attendant computational complexity. Many researchers have attempted optimizing the fuzzy control structure to improve the calculation efficiency. Shakouri et al. (1982) introduced a fuzzy regulator controller for a general multivariable system based on a state-space model. The simulation and real-time application results demonstrated the control robustness to modeling errors. Cheng et al. (1982, 1980) devised a concept of intersection coefficients and derived a formula in terms of these coefficients for multivariable fuzzy controllers. Czogala and Zimmermann (1984) and Czogala (1988) generalized these coefficients to random intersection coefficients and introduced a multi-dimensional probabilistic fuzzy control structure. A significant improvement in computational efficiency was illustrated through an example of a two-input two-output control system. Walichiewicz (1984) and Gupta et al. (1986) developed two fuzzy algorithms individually to simplify a multivariable fuzzy system into a set of one-dimensional systems. Lee et al. (1995, 1999) and Jeon and Lee (1995), defined an applicable index, which can be used to judge the simplicity of the decomposition method. The decomposition of multivariable control rules is helpful since it alleviates the complexity of the control action calculation and the fuzzy control structure is simplified without degrading the system performance. Raju et al. (1991) proposed a multi-level, hierarchically structured fuzzy controller, where the control actions were ranked according to the order of influence on the system. Linkens and Nyongesa (1996) introduced a simplified structure for a hierarchical multivariable fuzzy controller, which reduced the total number of rules as a linear function of the total number of system inputs.

Nevertheless, in many existing multivariable fuzzy control design methods, it is assumed that no cross-coupling effect exists among the multiple inputs and the outputs. These methods are only designed to reduce calculation complexity and usually lack the ability to eliminate the multivariable interaction effects. However, most of the real world multivariable systems have cross-coupled input–output relationships, and yet the multiple system outputs need to be controlled to achieve the desired set-points simultaneously. Lei and Langari (2000) developed a hierarchical fuzzy controller to stabilize a double inverted pendulum, where each subsystem was set up by ignoring the interactions and a higher level fuzzy coordinator was designed based on human intuition to compensate for subsystems interactions. By carefully choosing the control gains, better results were obtained than a conventional state feedback control strategy. Based on the physical analysis of the

* Corresponding author.
E-mail address: shin@purdue.edu (Y.C. Shin).

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controlled system, Lian and Huang (2001) designed a mixed fuzzy controller, which consisted of a set of regular fuzzy controllers and an appropriate decoupling fuzzy controller. The regular fuzzy controllers were set up for each degree of freedom of this multivariable system and the decoupling fuzzy controller was designed to handle the coupling effects among each input–output pair. Tu et al. (2000) proposed a multi-layer fuzzy logic controller, which was a combination of multiple multi-input single-output fuzzy controllers. The simulation results showed that the fuzzy control system was asymptotically stable in controlling a two-link cart-pole system. Koutb et al. (2004) introduced a multivariable fuzzy logic controller by integrating the input–output variables in a fuzzy relation that describes the physical plant's multivariable interactions. The scheme was tested on a nonlinear boiler-turbine process and achieved better control performance than conventional multiloop controllers. Mendonca et al. (2003) developed a multivariable fuzzy predictive control by incorporating fuzzy goals and constraints in an integrated fuzzy decision-making framework. Their simulation result for a container gantry crane showed satisfactory control performance. Sun and Li (2000) presented a multivariable fuzzy control system based on its fuzzy dynamic model. A standard fuzzy state feedback control law was developed for each local linear model and the multivariable cross-coupling effect was compensated by global fuzzy inferencing mechanism. The concept of connective subsystems was introduced to guarantee the overall stability of the closed-loop control system.

In the aforementioned multivariable fuzzy control strategies, fuzzy control rules are generated either based on human knowledge or the qualitative analysis of the multivariable systems to be controlled. Under the possible presence of nonlinearity and uncertainties, these fuzzy rules may not accurately represent the input–output relationship and thus deteriorate control performance. The stability of the closed-loop control systems cannot be guaranteed. Hence, a model-based multivariable fuzzy controller would be desirable to increase the accuracy of fuzzy control rules and improve the overall system performance.

The Relative Gain Array (RGA) concept has been studied by many researchers in the area of linear multivariable control (Sun and Li, 2000; Bristol, 1966; Gangopadhyay and Meckl, 2001; Persechini et al., 2004; Camacho and Rojas, 2000). Known as an interaction measure between multiple inputs and multiple outputs, each array element indicates the influence of a particular input to a specific output. To determine the relative gain array, only the system steady-state gains are required, from which the multivariable interaction degree can be obtained straightforwardly. The underlying idea of most existing multivariable control methods based on the relative gain array is to properly pair the manipulated variables with the control outputs, and then design a decoupling controller to decompose the multivariable interaction effect. A standard conventional controller, such as a Proportional-Integral-Derivative (PID) controller, can be designed for each Single-Input Single-Output (SISO) control loop. The shortcoming of this decoupling method is its sensitivity to modeling error, which makes it unsuitable for real world applications. When a perfect system model is unobtainable, a difficulty in multivariable control design is inevitable, especially in the presence of time-varying parameters, disturbances and/or sensor noises.

In this study, a novel multivariable fuzzy control strategy is presented, which makes use of the fuzzy compositional property to determine multiple control actions simultaneously and eliminate the interaction effects of Multi-Input Multi-Output (MIMO) systems. In Section 2, a multivariable system is modeled as a Fuzzy Basis Function Network (FBFN) and the Relative Gain Array (RGA) analysis is performed correspondingly. A multivariable fuzzy controller is designed thereafter in Section 3. More specifically, an adaptation mechanism is embedded to adjust the control rule online. Furthermore, a perpendicular fuzzy control engine is developed to eliminate multivariable coupling effects based on the system RGA. Section 4 provides the stability analysis for the proposed multivariable closed-loop control system. Two simulation examples are presented in Section 5 to illustrate the efficacy and effectiveness of the fuzzy controller in eliminating interaction effects and dealing with unknown model variations, disturbances and sensor noise. Conclusions are presented in the last section.

2. Interaction analysis for a general MIMO nonlinear system

Consider a class of Multi-Input Multi-Output (MIMO) dynamic system with p inputs and q outputs. Assume each output only depends on the current inputs, historic inputs, and the histories of the output itself. Such kind of systems can be represented in an input–output format as

$$\begin{aligned} y_j(k) = f_j[&u_1(k-1), u_1(k-2), \ldots, u_1(k-m_1+1), u_1(k-m_1),\\ &\vdots\\ &u_p(k-1), u_p(k-2), \ldots, u_p(k-m_p+1), u_p(k-m_p),\\ &y_j(k-1), y_j(k-2), \ldots, y_j(k-n_j+1), y_j(k-n_j)] \end{aligned} \tag{1}$$

where $u_1, \ldots, u_p$ are p inputs to the system, y_j is the jth output, the indices $m_1, \ldots, m_p$ and n_j represent the system orders for the p inputs and the jth output. $f_j(\cdot)$ is a smooth function representing the system's nonlinear dynamics. A fuzzy basis function network (FBFN) (Lee and Shin, 2003) can be constructed to represent this multivariable system in the form of Eq. (2), since it has the ability to uniformly approximate any continuous nonlinear function to a prescribed accuracy with a finite number of basis functions (Wang and Mendel, 1992)

$$\begin{aligned} R^i{:}\text{IF } &u_1(k-1) = A^i_{11} \text{ AND } u_1(k-2) = A^i_{12} \text{ AND} \ldots \text{ AND } u_1(k-m_1) = A^i_{1m_1} \text{ AND}\\ &\vdots\\ &u_p(k-1) = A^i_{p1} \text{ AND } u_p(k-2) = A^i_{p2} \text{ AND} \ldots \text{ AND } u_p(k-m_p) = A^i_{pm_p} \text{ AND}\\ &y_j(k-1) = B^i_{j1} \text{ AND } y_j(k-2) = B^i_{j2} \text{ AND} \ldots \text{AND } y_j(k-n_j) = B^i_{jn_j}\\ &\text{THEN } y_j(k) = b^i_j \end{aligned} \tag{2}$$

where $R^i (i = 1, 2, \ldots, l)$ denotes the ith fuzzy rule, $A^i_{11}, \ldots, A^i_{1m_1}, \ldots, A^i_{p1}, \ldots A^i_{pm_p}, B^i_{j1}, \ldots, B^i_{jn_j}$ are the antecedent Gaussian membership functions and b^i_j represents the consequent singleton membership function. For any given crisp input vector

$$\begin{aligned} \mathbf{x} &= [x_1, \ldots, x_{m_1+\cdots+m_p+n_j}]^{\mathrm{T}}\\ &= [u_1(k-1), \ldots, u_1(k-m_1), \ldots, u_p(k-1), \ldots, u_p(k-m_p),\\ &\quad y_j(k-1), \ldots, y_j(k-n_j)]^{\mathrm{T}} \end{aligned}$$

the system output $y_j(k)$ can be obtained as

$$\begin{aligned} y_j(k) &= f_j(\mathbf{x}) = f_j(u_1(k-1), \ldots, u_1(k-m_1), \ldots, u_p(k-1), \ldots, u_p(k-m_p), y_j(k-1) \ldots, y_j(k-n_j))\\ &= \frac{\sum_{i=1}^{l} \left[b^i_j \left(\prod_{t_1=1}^{m_1} \mu_{A^i_{1t_1}}(u_1(k-t_1)) \right) \cdot \cdots \cdot \left(\prod_{t_p=1}^{m_p} \mu_{A^i_{pt_p}}(u_p(k-t_p)) \right) \left(\prod_{t_y=1}^{n_j} \mu_{B^i_{jt_y}}(y_j(k-t_y)) \right) \right]}{\sum_{i=1}^{l} \left[\left(\prod_{t_1=1}^{m_1} \mu_{A^i_{1t_1}}(u_1(k-t_1)) \right) \cdot \cdots \cdot \left(\prod_{t_p=1}^{m_p} \mu_{A^i_{pt_p}}(u_p(k-t_p)) \right) \left(\prod_{t_y=1}^{n_j} \mu_{B^i_{jt_y}}(y_j(k-t_y)) \right) \right]} \end{aligned}$$