Engineering Applications of Artificial Intelligence 25 (2012) 1537–1547

Contents lists available at SciVerse ScienceDirect

Engineering Applications of Artificial Intelligence

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

Multivariable self-organizing fuzzy logic control using dynamic performance index and linguistic compensators

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ARTICLE INFO

Article history:
Received 8 September 2011
Accepted 7 November 2011
Available online 7 December 2011

Keywords:
Fuzzy logic control
Self-organizing
Compensator
Multivariable system
Decoupled control

ABSTRACT

As far as fuzzy logic based multivariable control systems are concerned, it is not always an easy task to express control strategies in the form of related multi-situations to multi-actions control rules. Decoupled control is one possible and attractive strategy to simplify this problem. However, the control performance of the decoupled controller relies greatly on '*a prior*' knowledge of the system dynamics to build suitable compensators. This paper aims at introducing a new model-independent decoupled control architecture with the ability of on-line learning, which ensures a fast tracking performance. In this architecture, the dominating controller is developed using a new model-free Self-Organizing Fuzzy Logic Control (SOFLC) architecture whereby the Performance Index table is 'dynamic', of a free structure, and starting from no knowledge. Furthermore, a switching mode scheme, with a compensating action triggered by the interaction between the channels, is proposed to improve the tracking performance of the closed-loop system. A series of simulations are carried out on a two-input and two-output biomedical process, with the conclusion that the proposed control mechanism has the ability to deal with varying system dynamics and noise and is tolerant to the choice of the compensator gains effectively.

1. Introduction

In multivariable fuzzy logic control systems, the high dimensionality of the relational matrix (Liu, 2003; Scherer, 2009) leads not only to computational difficulties but also to memory overload (Watkins, 1995). Hence, it is important to simplify these systems by extracting the main input–output mappings, and to develop a corresponding controller for every input and output mapping to avoid the problem of fuzzy rule explosion (Jeon and Lee, 1995). In the general structure of decoupled control, traditional multiple Single-Input Single-Output (SISO) or Multi-Input Single-Output (MISO) sys are designed as dominating controllers to deal with each degree of freedom from each single independent loop; while appropriate compensators are incorporated to counteract the residual interactions between the various channels according to the characteristics of the system's interaction.

A significant amount of work has already been carried-out around the architectures of Single-Output fuzzy logic dominating controllers. Self-Organizing Fuzzy Logic Control (SOFLC) based systems have been shown to possess advantages when controlling uncertain, mathematically ill-understood, non-linear and time-varying systems, thanks to their on-line features and explicit model-free architecture. However, they can also suffer from drawbacks such as a high computation time and a high memory storage requirement, especially when they are applied to multivariable systems with a high dimension. Since its first introduction by Procyk and Mamdani (1979), the original fuzzy rules for the performance index measure have been left practically unaltered in their version of the Self-Organizing Fuzzy Logic Control (SOFLC). *A priori* system information is however required to design this Performance Index table either individually or in blocks of cells (Mahfouf et al., 2000; Procyk and Mamdani, 1979) in order to obtain a suitable learning mechanism for the particular process. Several studies have hitherto been carried-out in order to improve the original SOFLC performance, such as those associated with the on-line adjustment of the input/output scaling factors (Mahfouf et al., 2002), the adjustment of the learning factors using a fuzzy logic (Lian and Lin, 2005) and the off-line optimization of parameters using Genetic Algorithms (Pal and Pal, 2003). Replacing the whole Performance Index table inside SOFLC architecture is another way for improvement, such as in Mahfouf et al. (2003). They integrated the generalized predictive control (GPC) algorithm for on-line fuzzy rules generation. Due to the predictive characteristics of GPC, such hybrid

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doi:10.1016/j.engappai.2011.11.001

approach rewards the time-delay inherent inside SOFLC. More recently, neural-network based self-organizing systems seem to have retained the attraction of relating such self-organizing architectures to mathematical formulations and analyses tools more easily (Kumar et al., 2007; Quek et al., 2009). However, such hybrid structures do generally compromise the overall system's transparency, a feature which is paramount to fuzzy logic driven systems as they strive and usually succeed in translating 'natural language' (expert knowledge) into a mathematical model.

The dominating controllers' design faces the limitations as well since the interactions are unclear or unpredictable in most cases. Dealing with each degree of freedom without consideration of the interactions is one possible way to simplify the problem (Moon and Lee, 2003). It is feasible when the sub-systems are loosely interacted. Steady-state compensators (Bristol, 1966) in the form of relative gain arrays (RGA) are valuable and widely used tools for eliminating undesirable pairings between channels, especially effective for linear multivariable processes. Nevertheless, steady-state tools cannot provide direct information about control performance, especially when they ignore the dynamics of the closed-loop system. Hence, off-line pre-design using trial-and-error provides one possibility of improving the control performance (Mollov and Babuska, 2004). However, unpredicted interaction will undoubtedly degrade the control performance since the system cannot cope with changes in system dynamics adequately. The inclusion of an on-line adjustment scheme helps to tackle this problem and such related work can be found in Bagheri and Moghaddam (2009), Liu (2003), Ma (2007), Nounou and Rehman (2007), and Perez et al. (2007). The on-line optimization strategies include Fuzzy Logic Control (FLC) (Perez et al., 2007), adaptive scheme (Bagheri and Moghaddam, 2009; Liu, 2003), decoupling neural network (Bagheri and Moghaddam, 2009; Ma, 2007) and Auto Regression Moving Average (ARMA) model (Liu, 2003). The effectiveness of such on-line adjustment schemes has been demonstrated in simulations or practical environments. However, further improvements can still be made vis-à-vis the learning actions, the adjustment layers, and the set-point tracking speed.

In the light of the above, it can be concluded that further work is still needed to render the decoupled control systems more flexible and model-independent (less constrained). First, the ability of learning the unmodelled system dynamics (such as inaccurate decoupling from the roughly estimated compensating gains, the unpredicted variations of dominating I/O loops) is required for such further improvements, at least as far as tracking effectiveness with a low computational burden and even with the conditions of being free of any system model are concerned; secondly, almost all previous work considered the main controller and the compensator as two main separate components, without any inherent synergy between them.

Therefore, a new decoupled control structure for multivariable systems is proposed and developed in this paper. The SOFLC architecture is applied for the dominating controller design due to the merits discussed above. In order to avoid the limitations emanating from the pre-designed fixed Performance Index table which is included in the SOFLC architecture, the idea of a 'dynamic (on-line evolving) Performance Index table' is explored. In the compensator controller, the steady-state Relative Gain Array (RGA) is used to measure the interactions between channels. Specifically, in order to improve the tracking performance, an on/off switching mode of the compensators, which is determined by the system's instant tracking information, is also proposed.

The remainder of this paper is organized as follows: In Section 2, a standard RGA based decoupled control system is described. The design of the new self-organizing fuzzy logic controller with a dynamic performance index table is proposed as the dominating controller in Section 3, where the mechanism of building a simple control rule base without any *a priori* system information is described; Section 4 relates to the study of the strategy of deciding the switching mode of the RGA-based compensator. The simulation results on a two-input two-output biomedical process are presented in Section 5. Finally in Section 6, conclusions relating to this research study are given.

2. A classical decoupled control architecture

Consider a Two-Inputs and Two-Outputs system with a steady-state gain matrix G as follows:

$$G=\begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \tag{1}$$

Given that the I/O data pairs are appropriately selected using a predefined Relative Gain Array (RGA) matrix and detailed pairing rules in Skogestad and Postlethwaite (1996), the basic system configuration of the RGA based decoupled control is shown in Fig. 1. The controllers c_1 and c_2 are the dominating controllers which deal with the tracking task of each channel, respectively. The interactions between channels are compensated via the steady-state relative gains. For channel 1, the main control input u_{11} and the compensating input u_{12} are combined together to form the actual input u_1^* to the plant. Similar reasoning applies to the other channel.

The relationship between the dominating control inputs u_i and the actual plant control inputs u_1^* is given as follows:

$$\begin{bmatrix} u_1^* \\ u_2^* \end{bmatrix}=\begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix}\begin{bmatrix} u_1 \\ u_2 \end{bmatrix}=\begin{bmatrix} 1 & -\frac{g_{12}}{g_{11}} \\ -\frac{g_{21}}{g_{22}} & 1 \end{bmatrix}\begin{bmatrix} u_1 \\ u_2 \end{bmatrix}=\Lambda\begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \tag{2}$$

where the matrix

$$\Lambda=\begin{bmatrix} 1 & -\frac{g_{12}}{g_{11}} \\ -\frac{g_{21}}{g_{22}} & 1 \end{bmatrix}$$

is called the compensation matrix, which can be specified by Skogestad and Postlethwaite (1996). It is clear that the control performance of the decoupled controller relies on *a prior* knowledge of the system dynamics greatly. The paper will aim to make the system more flexible and effective based on such a decoupled architecture.

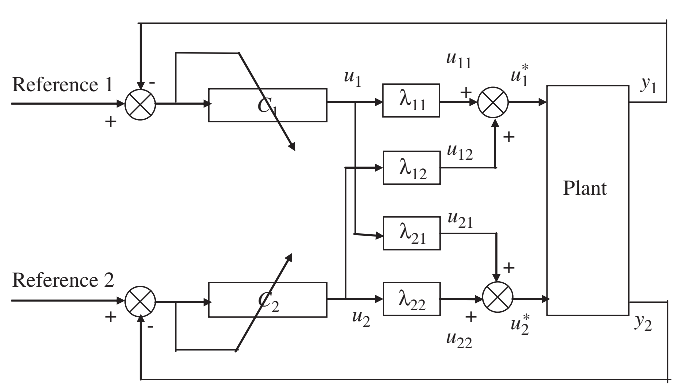

Fig. 1. A 2×2 decoupled system using RGA compensators.