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Grey Wolf Optimizer-Based Approach to the Tuning of PI-Fuzzy Controllers with a Reduced Process Parametric Sensitivity

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Abstract: This paper suggests the use of Grey Wolf Optimizer (GWO) algorithms to tune the parameters of Takagi-Sugeno proportional-integral-fuzzy controllers (PI-FCs) for a class of nonlinear servo systems. The servo systems are modelled by second order dynamics plus a saturation and dead zone static nonlinearity. The GWO algorithms solve the optimization problems that minimize discrete-time objective functions expressed as the weighted sum of the squared control error and of the squared output sensitivity function in order to achieve the parametric sensitivity reduction. The output sensitivity function is derived from the sensitivity model with respect to the modification of the process gain, and fuzzy control systems with a reduced process gain sensitivity are offered. Three parameters of Takagi-Sugeno PI-FCs are obtained by a new cost-effective tuning approach. Experimental results related to the angular position control of a laboratory servo system validate the tuning approach.

Keywords: Grey Wolf Optimizer, optimization problems, parametric sensitivity, real-time experiments, Takagi-Sugeno PI-fuzzy controllers, servo systems.

1. INTRODUCTION

The systematic design and tuning of fuzzy control systems (CSs) can guarantee the desired/imposed performance specifications (Bernal et al., 2011; Guelton et al., 2010; Ruano et al., 2014). The performance specifications can be expressed by means of empirical performance indices (overshoot, settling time, rise time, etc.) and of objective functions (o.f.s) in various optimization problems (o.p.s).

Solving the o.p.s specific to the optimal tuning of fuzzy controllers (FCs) is complicated due to the o.f.s and the risk of getting trapped in local minima. Nature-inspired optimization algorithms can be employed to minimize these o.f.s because of their reduced computational cost, transparent and cost-effective design and implementation, and derivative-free operation (i.e., gradient information replaced by actual o.f. value). Such algorithms include the popular swarm intelligence algorithms, which can be also viewed as softmax exploration strategies in the context of reinforcement learning or directed random search algorithms.

This paper is related to the control of servo systems that are modelled by second order dynamics plus a saturation and dead zone static nonlinearity. Some recent applications of swarm intelligence algorithms to the optimal tuning of the parameters of FCs for servo systems include Particle Swarm Optimization (PSO) (Bouallègue et al., 2012; Castillo and Melin, 2014) and Gravitational Search Algorithm (GSA) in several versions (Precup et al., 2011).

As shown in (Mirjalili et al., 2014), the Grey Wolf Optimizer (GWO) algorithm is developed by mimicking grey wolf social hierarchy and hunting habits. The social hierarchy is simulated by categorizing the population of search agents into four types of individuals, namely alpha, beta, delta and omega, based on their fitness. The search process is modelled using the hunting behaviour of grey wolfs making use of three stages, i.e., searching, encircling and attacking the prey. The first two stages are dedicated to exploration the last one covers the exploitation stage.

This paper suggests two new contributions. First, the application of GWO algorithms to the optimal tuning of Takagi-Sugeno PI-FCs is given. The GWO algorithms solve the o.p.s that minimize discrete-time o.f.s expressed as the weighted sum of the squared control error and of the squared output sensitivity function. Second, since the variables of these o.f.s are the tuning parameters of Takagi-Sugeno PI-FCs, a GWO-based tuning approach for fuzzy CSs is offered. Both contributions lead to fuzzy CSs with a reduced process gain sensitivity and are advantageous with respect to the state-of-the-art by the reduced number of search parameters, their adaptive values in the GWO algorithms and the cost-effective tuning approach.

This paper is organized as follows: the o.p.s that ensure the tuning of fuzzy CSs with a reduced process parametric sensitivity are defined in the next section. The GWO algorithms and the cost-effective GWO-based tuning approach are presented in Section 3. Section 4 treats a case study that deals with the angular position control of a

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laboratory servo system and experimental results are included. The conclusions are pointed out in Section 5.

2. OPTIMIZATION PROBLEMS FOR FUZZY CONTROL SYSTEMS WITH A REDUCED PARAMETRIC SENSITIVITY

The fuzzy CS structure is given in Fig. 1, where FC is the fuzzy controller, P is the process, F is the set-point filter, r is the reference input (the set-point), r_1 is the filtered reference input, d is the disturbance input, y is the controlled output, u is the control signal, $e = r_1 - y$ is the control error, $\boldsymbol{\alpha}$ is the process parameter vector, and ρ is the controller parameter vector. The parameters of both FC and F can be tuned as shown in Fig. 1, which illustrates a of two-degree-of-freedom (2-DOF) CS structure, i.e., a set-point filter one.

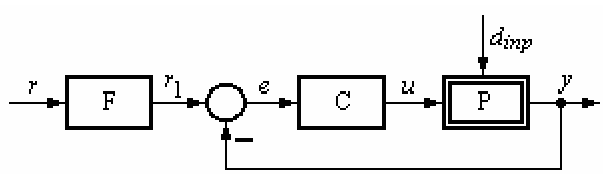

Fig. 1. Fuzzy control system structure.

The state-space model of P that characterizes the accepted nonlinear servo systems according to (David, 2015) is

$$m(t) = \begin{cases} -1, & \text{if } u(t) \le -u_b, \\ [u(t)+u_c]/(u_b-u_c), & \text{if } -u_b < u(t) < -u_c, \\ 0, & \text{if } -u_c \le |u(t)| \le u_a, \\ [u(t)-u_a]/(u_b-u_a), & \text{if } u_a < u(t) < u_b, \\ 1, & \text{if } u(t) \ge u_b, \end{cases}$$
$$\begin{bmatrix} \dot{\alpha}(t) \\ \dot{\omega}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & -1/T_\Sigma \end{bmatrix} \begin{bmatrix} \alpha(t) \\ \omega(t) \end{bmatrix} + \begin{bmatrix} 0 \\ k_P/T_\Sigma \end{bmatrix} m(t) + \begin{bmatrix} 1 \\ 0 \end{bmatrix} d(t), \tag{1}$$
$$y(t) = [1 \quad 0][\alpha(t) \quad \omega(t)]^T,$$

where $t \ge 0$ is the continuous time argument, $k_P > 0$ is the process gain, $T_\Sigma > 0$ is the small time constant, the control signal applied to the direct current (DC) motor u is a pulse width modulated duty cycle, $\alpha(t)$ is the angular position, $\omega(t)$ is the angular speed, and the superscript T indicates matrix transposition. The variable m is the output of the saturation and dead zone static nonlinearity, which is modelled by the first equation in (1) with the parameters u_a, u_b and u_c, $0 < u_a < u_b$, $0 < u_c < u_b$. The model (1) includes the actuator and measurement instrumentation dynamics.

The nonlinearity in (1) is neglected in the simplified model of the process expressed as the transfer function (t.f.) $P(s)$ from the input u to the output y:

$$P(s) = k_{EP}/[s(1+T_\Sigma s)], \tag{2}$$

with k_{EP} – the equivalent process gain defined as

$$k_{EP} = \begin{cases} k_P/(u_b - u_c), & \text{if } -u_b < u(t) < -u_c, \\ k_P/(u_b - u_a), & \text{if } u_a < u(t) < u_b. \end{cases} \tag{3}$$

The t.f. $P(s)$ can be used in both the linear and the FC design and tuning in two cases out of the five cases concerning the nonlinearity outlined in (1). As shown in (David, 2015), PI controllers can deal with the process modelled in (1) using Fig. 1 with a PI controller instead of FC. The t.f. of the PI controller is

$$C(s) = k_c(1+sT_i)/s = k_C[1+1/(sT_i)], \; k_C = k_c T_i, \tag{4}$$

where $k_C > 0$ (or $k_c > 0$) is the controller gain and $T_i > 0$ is the integral time constant.

Accepting that the process parameters k_P and T_Σ are variable, the expression of the process parameter vector is

$$\alpha = [\alpha_1 \quad \alpha_2]^T = [k_P \quad T_\Sigma]^T, \tag{5}$$

the definitions of the state sensitivity functions λ_υ, $\upsilon = 1...n$, and of the output sensitivity function σ are

$$\lambda_\upsilon = \left[\frac{\partial x_\upsilon}{\partial \alpha_j}\right]_0, \; \sigma = \left[\frac{\partial y}{\partial \alpha_j}\right]_0, \; \upsilon = 1...n, \; j \in \{1,2\}, \tag{6}$$

where the subscript 0 indicates the nominal value of the process parameter α_j, $j \in \{1,2\}$, and n is the number of state variables of the fuzzy CS.

Equation (6) is employed to derive the state sensitivity models of the fuzzy CS with respect to α_j (David, 2015), with $n = 4$ for the process (1) controlled by Takagi-Sugeno PI-FCs.

The o.p. that ensures the sensitivity reduction with respect to the modifications of α_j is

$$\boldsymbol{\rho}^* = \arg\min_{\boldsymbol{\rho} \in D_{\boldsymbol{\rho}}} J(\boldsymbol{\rho}), \; J(\boldsymbol{\rho}) = \sum_{t_d=0}^{\infty} \{e^2(t_d, \boldsymbol{\rho}) + \gamma^2[\sigma(t_d, \boldsymbol{\rho})]^2\}, \tag{7}$$

where γ is the weighting parameter, ρ^* is the optimal controller parameter vector, i.e., the optimal value of the vector ρ, $D_{\boldsymbol{\rho}}$ is the feasible domain of ρ, $J(\rho)$ is the o.f., and $t_d \in \mathbf{Z}$, $t_d \ge 0$, is the discrete time. Stability constraints can be used (Bernal et al., 2011; Guelton et al., 2010; Lam and Lauber, 2013; Precup et al., 2009).

3. GWO-BASED ALGORITHMS AND TUNING APPROACH

As mentioned in (Mirjalili et al., 2014), the GWO algorithms start with the initialization of the agents comprising the pack. Use is made of a total number of N agents (i.e., grey wolves), each agent having a position vector $\mathbf{X}_i$ associated with them

$$\mathbf{X}_i = [x_i^1 \quad ... \quad x_i^f \quad ... \quad x_i^q]^T, \; i = 1...N, \tag{8}$$