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Novel Adaptive Charged System Search algorithm for optimal tuning of fuzzy controllers

Radu-Emil Precup [a,*], Radu-Codruţ David [a], Emil M. Petriu [b], Stefan Preitl [a], Mircea-Bogdan Rădac [a]

[a] "Politehnica" University of Timisoara, Department of Automation and Applied Informatics, Bd. V. Parvan 2, RO-300223 Timisoara, Romania
[b] University of Ottawa, School of Electrical Engineering and Computer Science, 800 King Edward, Ottawa, ON K1N 6N5, Canada

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ABSTRACT

This paper proposes a novel Adaptive Charged System Search (ACSS) algorithm for the optimal tuning of Takagi–Sugeno proportional–integral fuzzy controllers (T–S PI-FCs). The five stages of this algorithm, namely the engagement, exploration, explanation, elaboration and evaluation, involve the adaptation of the acceleration, velocity, and separation distance parameters to the iteration index, and the substitution of the worst charged particles' fitness function values and positions with the best performing particle data. The ACSS algorithm solves the optimization problems aiming to minimize the objective functions expressed as the sum of absolute control error plus squared output sensitivity function, resulting in optimal fuzzy control systems with reduced parametric sensitivity. The ACSS-based tuning of T–S PI-FCs is applied to second-order servo systems with an integral component. The ACSS algorithm is validated by an experimental case study dealing with the optimal tuning of a T–S PI-FC for the position control of a nonlinear servo system.

1. Introduction

The design and tuning of optimal control systems is often based on linear or linearized models of the controlled processes. However, in real life situations, many processes are subjected to parametric variations which result in models that are either nonlinear or only locally linearized around several nominal operating points or trajectories. In order to solve the problems occurring in these situations, a sensitivity analysis with respect to the parametric variations of the controlled processes is required.

As shown in Rosenwasser and Yusupov (2000), the uncontrollable process parametric variations lead to undesirable behaviors of the control systems. While the fundamental deviation of a control system relative to its nominal trajectory is described by the control error, the additional deviation can be described by the output sensitivity function in the sensitivity model.

Solving the optimization problem for the usually non-convex objective functions used in many control systems is not a trivial task as it can lead to several local minima (Angelov & Yager, 2013; Bayam, Liebowitz, & Agresti, 2005; Blažič et al., 2013; Horváth & Rudas, 2004; Iliadis, Kitikidou, & Skoularik, 2012; Linda & Manic, 2011; Srivastava, Chis, Deb, & Yang, 2012). Fuzzy control, as a relatively easily understandable nonlinear control strategy, is successfully embedded in these optimization problems as a convenient way to solve the systematic design and tuning of these control systems (Castillo & Melin, 2012;Chiang & Liu, 2012; Feng, 2006; Precup & Hellendoorn, 2011;Precup et al., 2012c; Škrjanc, Blažič, & Agamennoni, 2005). The optimal tuning of fuzzy controllers allows them to cope with non-convex or non-differentiable objective functions due to controllers' structures and nonlinearities, and to process complexity, which can lead to multi-objective optimization problems. Some current evolutionary-based optimization approaches to the parameter tuning of fuzzy control systems include genetic algorithms (Onieva, Milanés, Villagrá, Pérez, & Godoy, 2012; Pérez, Milanés, Godoy, Villagrá, & Onieva, 2013), Simulated Annealing (Precup, David, Petriu, Preitl, & Rădac, 2012a; Jain, Sivakumaran, & Radhakrishnan, 2011), Particle Swarm Optimization (PSO) (Bingül & Karahan, 2011; Oh, Jang, & Pedrycz, 2011; Precup et al., 2013a), Gravitational Search Algorithms (GSAs) (Precup, David, Petriu, Preitl, & Rădac, 2012b; Precup et al., 2013a), Ant Colony Optimization (Chang, Chang, Tao, Lin, & Taur, 2012), cross-entropy (Haber, del Toro, & Gajate, 2010), migration algorithms (Vaščák, 2012), chemical optimization (Melin, Astudillo, Castillo, Valdez, & Garcia, 2013), Charged System Search (CSS) algorithms (Precup, David, Petriu, & Preitl, 2011), etc., in several fuzzy control system structures. The appropriate tools specific to fuzzy systems (Ahmed, Shakev, Topalov, Shiev, & Kaynak, 2012; Akın, Khaniyev, Oruç, & Türkşen, 2013; Baranyi et al., 2002; Göleç, Murat, Tokat, & Türkşen, 2012; Johanyák, 2010; Precup et al., 2013a;

* Corresponding author. Tel.: +40 256 40 32 29/30/26; fax: +40 256 40 3214.
E-mail addresses: radu.precup@aut.upt.ro (R.-E. Precup), davidradu@gmail.com (R.-C. David), petriu@eecs.uottawa.ca (E.M. Petriu), stefan.preitl@aut.upt.ro (S. Preitl), mircea.radac@aut.upt.ro (M.-B. Rădac).

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Teodorescu, 2012; Tikk, Johanyák, Kovács, & Wong, 2011) must be applied in all situations.

Building upon our recent CSS algorithm for the optimal tuning of fuzzy controllers (Precup et al., 2011) this paper proposes a novel Adaptive Charged System Search (ACSS) algorithm for the optimal tuning of the fuzzy controllers for servo systems. The search ability of this algorithm is based on the interactions between charged particles (CPs) that are moving through a predefined domain. The CPs are also referred to as agents.

Due to the good balance between exploration and exploitation offered by the CSS algorithms, they can conveniently be used to solve discrete and continuous optimization problems with non-convex objective functions which eventually have several local minima.

The proposed ACSS algorithm consisting of five stages: engagement, exploration, explanation, elaboration and evaluation, is inspired by the adaptive staged PSO algorithm (Liu, Tan, & He, 2010) and extended using the 5-E learning cycle (Bybee, 1997). It has the following functional characteristics:

- The acceleration parameter is adapted to the iteration index such that to decrease the acceleration parameter with respect to the iteration index.
- The velocity parameter is adapted to the iteration index such that to increase the velocity parameter with respect to the iteration index.
- The parameter in the separation distance meant for the avoidance of singularities is adapted to the iteration index such that to increase the separation index with respect to the iteration index.
- Agents' worst fitness function values and positions are reset to their best values at each run of the ACSS.

These characteristics of the ACSS algorithm lead to a more efficient exploration of search space and to better objective function values than those provided by the non-adaptive CSS algorithms (Kaveh & Talatahari, 2010a; Kaveh & Talatahari, 2010b; Kaveh & Talatahari, 2012; Precup et al., 2011). The proposed algorithm allows for an efficient search procedure in the optimal fuzzy tuning needed for the fuzzy control of the complex servo systems where several minima and non-convexity can arise.

Building upon our recent contributions to the optimal tuning of Takagi–Sugeno proportional–integral fuzzy controllers (T–S PI-FCs), the new ACSS algorithm proposed in this paper allows solving an optimization problem with objective functions expressed as discrete-time weighted sums of absolute control error plus squared output sensitivity function with respect to process gain variations. The optimal tuning of T–S PI-FCs is then discussed for the representative case of the nonlinear servo systems modeled by second-order systems with an integral component. The minimization of the objective functions leads to fuzzy control systems with a reduced process gain sensitivity, which allow for the use of simplified models in controller design and tuning.

The paper is structured as follows: the novel ACSS algorithm is presented in Section 2. The original design and tuning method for optimal T–S PI-FCs dedicated to servo systems modeled by second-order systems with an integral component is discussed in Section 3. Section 4 discusses the case study dealing with the optimal tuning of a T–S PI-FC for the angular position control of an experimental laboratory DC servo system. The conclusions are presented in Section 5.

2. Adaptive Charged System Search algorithm

The search ability of the CSS algorithm is based on the interactions between charged particles (CPs), that are moving through a predefined domain, starting with arbitrary determined initial positions with null primary velocities.

A charged particle CP is characterized by its electric charge

$$q_i = (f_i - f_{best})/(f_{best} - f_{worst}), \quad i = 1, \ldots, N, \tag{1}$$

where f_i is the objective function value or the fitness function value of the ith CP, f_{best} and f_{worst} are the best and the worst fitness of all CPs, and N is the total number of CPs. The separation distance between two CPs is defined as

$$r_{ij} = (\|\mathbf{X}_i\| - \|\mathbf{X}_j\|)/[\|0.5(\mathbf{X}_i + \mathbf{X}_j) - \mathbf{X}_{best}\| + \varepsilon], \mathbf{X}_i, \mathbf{X}_j, \mathbf{X}_{best} \in \mathbf{R}^N, \tag{2}$$

where $\mathbf{X}_i$ and $\mathbf{X}_j$ are the positions of ith and jth CP, respectively, $\mathbf{X}_{best}$ is the position of the best current CP, and the relatively small parameter $\varepsilon > 0$ is introduced to avoid singularities.

From the point of view of the electric forces between interacting particles there are "good" CPs which attract other particles, and "bad" CPs, which repel other particles, as specified by the coefficient c_{ij}:

$$c_{ij} = \begin{cases} -1 & \text{if } f_i < f_j, \\ 1 & \text{otherwise}. \end{cases} \tag{3}$$

When a "good" CP attracts a bad one, the algorithm is in the exploitation stage, while when a "bad" CP repels a good one, the algorithm is in the exploration stage.

The resultant electrical force $\mathbf{F}_j$ acting on the jth CP, is considered as a charged sphere with radius a having a uniform volume charge density:

$$\begin{aligned} &\mathbf{F}_j = q_j \sum_{i=1, i\neq j}^{N} \left[q_i c_{ij} \left(r_{ij} i_1 / a^3 + i_2 / r_{ij}^2 \right) (\mathbf{X}_i - \mathbf{X}_j) \right], \\ &i_1 = 0, i_2 = 1 \iff r_{ij} \geqslant a, i_1 = 1, i_2 = 0 \iff r_{ij} < a, j = 1 \ldots N. \end{aligned} \tag{4}$$

The updated position $\mathbf{X}_j(k+1)$ and velocity $\mathbf{V}_j(k+1)$ of the jth CP, is (Kaveh & Talatahari, 2010a; Kaveh & Talatahari, 2010b; Kaveh & Talatahari, 2012; Precup et al., 2011):

$$\begin{aligned} &\mathbf{X}_j(k+1) = r_{j1} k_a (\mathbf{F}_j / m_j)(\Delta t)^2 + r_{j2} k_v \mathbf{V}_j(k) \Delta t + \mathbf{X}_j(k), \\ &\mathbf{V}_j(k+1) = [\mathbf{X}_j(k+1) - \mathbf{X}_j(k)]/\Delta t, \end{aligned} \tag{5}$$

where k is the current iteration index, k_a is the acceleration parameter, k_v is the velocity parameter, r_{j1} and r_{j2} are two random numbers uniformly distributed in the range of (0, 1), m_j is the mass of jth CP, $m_j = q_j$ according to (Kaveh & Talatahari, 2010a) and Δt is the time step, set to 1.

The effect of previous velocity and the resultant force acting on a CP can be decreased or increased on the basis of the values of k_v and k_a, respectively.

While an exhaustive search carried on in the early iterations may improve the exploration performance, a gradual decrease of k_v and k_a is advised in Kaveh and Talatahari (2010a), Kaveh and Talatahari (2010b) and Kaveh and Talatahari (2012). Since k_a is the parameter related to the attracting forces, selecting a large value for this parameter may cause a fast convergence and choosing a small value can increase the computational time. In fact, k_a is a control parameter of the exploitation; therefore, choosing an incremental function can improve the performance of the algorithm. In addition, the direction of $\mathbf{V}_j(k)$ is not necessarily the same as that of $\mathbf{F}_j$. Thus, it can be concluded that the velocity parameter k_v controls the exploration process, so an increasing function can be selected. Therefore, based on extended experimental practice, we suggest the following modifications of k_a and k_v with respect to the iteration index:

$$k_a = 3(1 - k/k_{\max}), \quad k_v = 0.5(1 + k/k_{\max}), \tag{6}$$

where $k_{\max}$ is the maximum number of iterations.