Applied Soft Computing 38 (2016) 75–86

Contents lists available at ScienceDirect

Applied Soft Computing

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

Control strategy PSO

Wei Zhang*, Jiao Liu, Lv-bin Fan, Ya-hong Liu, Di Ma

College of Chemistry and Chemical Engineering, Taiyuan University of Technology, Taiyuan 030024, PR China

ARTICLE INFO

Article history:
Received 2 February 2013
Received in revised form
18 September 2015
Accepted 25 September 2015
Available online 9 October 2015

Keywords:
Particle swarm optimization
Parameter selection
Evaluation index
Control theory

ABSTRACT

Many variants of particle swarm optimization (PSO) both enhance the performance of the original method and greatly increase its complexity. Motivated by this fact, we investigate factors that influence the convergence speed and stability of basic PSO without increasing its complexity, from which we develop an evaluation index called "Control Strategy PSO" (CSPSO). The evaluation index is based on the oscillation properties of the transition process in a control system. It provides a method of selection parameters that promote system convergence to the optimal value and thus helps manage the optimization process. In addition, it can be applied to the characteristic analyses and parameter confirmation processes associated with other intelligent algorithms. We present a detailed theoretical and empirical analysis, in which we compare the performance of CSPSO with published results on a suite of well-known benchmark optimization functions including rotated and shifted functions. We used the convergence rates and iteration numbers as metrics to compare simulation data, and thereby demonstrate the effectiveness of our proposed evaluation index. We applied CSPSO to antenna array synthesis, and our experimental results show that it offers high performance in pattern synthesis.

© 2015 Elsevier B.V. All rights reserved.

1. Introduction

Motivated by the social behavior of flocks of birds and schools of fish, particle swarm optimization (PSO) is a stochastic process that is an efficient, robust, and simple optimization algorithm for finding optimal regions of complex search spaces. PSO uses a set of particles that represent the potential solutions needed to solve an optimization problem. The particle moves toward an optimal solution based on its present velocity and its individual best position found at each iteration, while also incorporating the globally best solution found by its companion particles. The position and the velocity relationship after the kth iteration are obtained by the following update formula:

$$v[k+1] = \omega \cdot v[k] + c_p \cdot r_p[k] \cdot (p[k] - x[k]) + c_g \cdot r_g[k] \cdot (g[k] - x[k]) \quad (1)$$

$$x[k+1] = x[k] + v[k+1] \quad (2)$$

where ω is a constant in the range (0, 1) called the inertia weight; c_p and c_g represent the acceleration factors, which denote the cognition and social learning factors, respectively; r_p and r_g are two independent uniform random numbers, different from each other, and generally distributed between 0 and 1; $p[k]$ is the best previous position of $x[k]$; and $g[k]$ is the best overall position achieved by a particle within the entire population.

To gain deeper insight into the mechanism of PSO, many theoretical analyses have been conducted on the algorithm, and most of these works have focused on the behavior of a single particle in PSO, analyzing the particle's trajectory or stability using deterministic or stochastic methods [1–6]. To view PSO from a new perspective, we constructed a relationship between the dynamic process of PSO and the transition process of a control system in order to identify factors that influence the convergence speed and stability of basic PSO without increasing the algorithm's complexity.

The outline of this paper is organized as follows. In Section 2, we summarize significant previous developments regarding the original PSO method. In Section 3, we propose a theoretical analysis for convergence in a standard PSO according to control theory. A comparative analysis of our control strategy PSO, which incorporates the opinions of Jiang and Fernández-Martínez, is presented in Section 4. The experimental environment and data analysis are described in Section 5. Section 6 discusses the application of this new strategy to antenna array pattern synthesis. Finally, we draw conclusions and describe our plans for future research in Section 7.

2. Previous work on particle swarm optimization

It is well known that both exploration and exploitation activities are necessary to achieve optimization using the PSO algorithm. In

* Corresponding author. Tel.: +86 13934212849.
E-mail address: zhangwei01@tyut.edu.cn (W. Zhang).

http://dx.doi.org/10.1016/j.asoc.2015.09.030
1568-4946/© 2015 Elsevier B.V. All rights reserved.

practice, exploration and exploitation contradict each other, and therefore premature convergence will occur when these activities are not balanced properly. So, to achieve good performance with PSO, many theoretical analyses and improved algorithms have been proposed. Shi and Eberhart [7] first incorporated the concept of inertia weight into the original PSO algorithm to balance local and global searching during the optimization process. They concluded that the PSO with an inertia weight in the range [0.9, 1.2] will have a better performance on average. Some researchers have also attempted to simulate particle trajectories by directly sampling the particles using a random number generator with a certain probability distribution. For instance, Clerc and Kennedy [1] mathematically analyzed the stochastic behavior of the PSO algorithm in stagnation and introduced a PSO variant with a constriction factor. Later, they compared the performance of the PSO with inertia weight and a constriction factor [3]. In addition, Kennedy [8] proposed a type of PSO where the usual velocity formula was replaced by samples from a Gaussian distribution. To avoid premature convergence of PSO, Chen et al. [9] developed a novel hybrid optimization method, called the hybrid PSO–EO algorithm, which combines PSO with extremal optimization (EO). Sun et al. [10] proposed quantum-behaved particle swarm optimization (QPSO) as well as additional algorithms that improved QPSO. Although similar variants were continually devised [11–14], most of the improved PSO methods increased the complexity of the algorithm. This need not be the case, however, and Pedersen and Chipperfield [15] presented a simplified PSO called many optimizing liaisons (MOL) which is similar to “social-only” PSO: the only difference was that the search range would be decreased for all dimensions simultaneously by multiplying with a factor for each failure to improve the fitness.

Accelerating the convergence speed and avoiding the local optimal solution are two main goals in PSO research. Many factors affect the convergence properties and performance of the PSO algorithm, such as population size, velocity clamping, position clamping, topology of the neighborhood, synchronous or asynchronous updates. Among these factors, the values of the inertia weight and the acceleration coefficient may significantly impact the efficiency and reliability of the PSO. Properly selecting these two parameters can improve the convergence rate of PSO using a smaller number of particles as well as increase the operation speed.

Some theoretical analyses of particle trajectories have provided insight into how the particle swarm system works. Eberhart and Shi [3] empirically found that an inertia weight of 0.729 and an acceleration coefficient of 1.496 are good parameter choices that led to convergent trajectories. Trelea [4] analyzed the dynamic behavior and convergence of the standard PSO algorithm using standard results from discrete-time dynamical system theory and provided a parameter set in the algorithm convergence domain. Jiang et al. [6] studied the stochastic convergence properties of the standard PSO algorithm and came up with a condition that ensures stochastic convergence of the particle swarm system. Then, according to the results of their analysis, Jiang et al. [5] suggested a set of PSO parameters. In their study, Fernández-Martínez et al. [16] proposed some promising parameter sets and established a range for the inertia value and acceleration coefficients after investigating the properties of the variance and covariance of second-order moments. In subsequent studies, Chen and Jiang [17] proposed a statistical interpretation of particle swarm optimization in order to capture the stochastic behavior of the entire swarm. They suggested an acceleration coefficient that combines the effects of both the inertia weight and the common acceleration coefficient for the neighborhood of the global best position.

The aforementioned reports use mathematical analyses to provide insight into how a particle swarm system works. The oscillation properties of PSO also influence the optimization process, but few reports have focused on analyzing these properties from a control theory perspective. Both the No Free Lunch Theorem [18] and the Optimal Contraction Theorem [19] indicate that no optimization method will be optimal for arbitrary problems, and a balance between exploitation and exploration in PSO is desirable for all problems. To enhance the searching ability of PSO and to accelerate its convergence, we performed a detailed theoretical and empirical analysis and propose a parameter selection scheme based on control theory.

3. Dynamic characteristic analysis based on control theory

To improve convergence performance, it is necessary to analyze the behavior of particle trajectories. By substituting Eq. (1) into Eq. (2), the following nonhomogeneous recurrence relation is obtained:

$$x[k+1]+(c_p\cdot r_p[k]+c_g\cdot r_g[k]-1-\omega)\cdot x[k]+\omega\cdot x[k-1] = c_p\cdot r_p[k]\cdot p[k]+c_g\cdot r_g[k]\cdot g[k] \quad (3)$$

Eq. (4) is obtained by applying the expectation operator to both sides of Eq. (3):

$$Ex[k+2]+\left(\frac{c_p+c_g}{2}-1-\omega\right)\cdot Ex[k+1]+\omega\cdot Ex[k] = \frac{c_p\cdot p[k]+c_g\cdot g[k]}{2} \quad (4)$$

According to the z-transform of Eq. (4), the corresponding characteristic equation is

$$z^2+\left(\frac{c_p+c_g}{2}-\omega-1\right)z+\omega=0 \quad (5)$$

which has the complex eigenvalues given by

$$z_{1,2}=\frac{1+\omega-((c_p+c_g)/2)\pm j\sqrt{4\omega-(((c_p+c_g)/2)-\omega-1)^2}}{2} \quad (6)$$

where j is the imaginary unit, and the stability condition is given by

$$|z_{1,2}|<1 \quad (7)$$

According to the time-domain analysis of linear control systems, the complex eigenvalues of Eq. (6) in the z-plane can be expressed as

$$z_{1,2}=e^{-\xi\omega_n\pm j\omega_n\sqrt{1-\xi^2}} \quad (8)$$

where ω_n is the natural frequency and ξ $(0<\xi<1)$ is the damping ratio of the control system. Both parameters are characteristics of the PSO algorithm itself. The decay rate and amplitude of the transient component depend on ω_n and ξ. The maximum overshoot M denotes the maximum peak value of the response, which is decided by a system's damping degree, such that the greater the value of ξ, the smaller the maximum overshoot.

$$M=e^{\frac{-\pi\xi}{\sqrt{1-\xi^2}}}\times 100\% \quad (9)$$

The characteristics of Eqs. (8) and (9) can be summarized as follows:

(1) Lower $|z_{1,2}|$ values lead to faster convergence, while higher values result in unstable motion and slower convergence. The convergence rate becomes slower when the value of $|z_{1,2}|$ approaches 1 and continuous oscillation occurs when $|z_{1,2}|$=1. Thus, higher $|z_{1,2}|$ values enable the swarm to cover a wider region of the search space. Lower $|z_{1,2}|$ values are beneficial in the later stages of searching, when faster convergence is preferable.

(2) The dynamic characteristic $Ex(k)$, which is decided by the complex eigenvalues, is a sinusoidal oscillation with a natural

Download English Version:

https://daneshyari.com/en/article/494850

Download Persian Version:

https://daneshyari.com/article/494850

Daneshyari.com