Available online at www.sciencedirect.com
ScienceDirect
Applied Soft Computing 7 (2007) 1019–1026
Applied Soft Computing
www.elsevier.com/locate/asoc

Chaotic dynamic characteristics in swarm intelligence

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Received 27 April 2006; received in revised form 31 July 2006; accepted 17 October 2006
Available online 13 November 2006

Abstract

Swarm intelligence (SI) is an innovative distributed intelligent paradigm whereby the collective behaviors of unsophisticated individuals interacting locally with their environment cause coherent functional global patterns to emerge. The intelligence emerges from a chaotic balance between individuality and sociality. The chaotic balances are a characteristic feature of the complex system. This paper investigates the chaotic dynamic characteristics in swarm intelligence. The swarm intelligent model namely the particle swarm (PS) is represented as an iterated function system (IFS). The dynamic trajectory of the particle is sensitive on the parameter values of IFS. The Lyapunov exponent and the correlation dimension are calculated and analyzed numerically for the dynamic system. Our research results illustrate that the performance of the swarm intelligent model depends on the sign of the maximum Lyapunov exponent. The particle swarm with a high maximum Lyapunov exponent usually achieves better performance, especially for multi-modal functions.

Keywords: Swarm intelligence; Chaos; Particle swarm; Iterated function system

1. Introduction

Swarm intelligence (SI) is mainly inspired by social behavior patterns of organisms that live and interact within large groups of unsophisticated autonomous individuals. In particular, it incorporates swarming behaviors observed in flocks of birds, schools of fish, or swarms of bees, colonies of ants, and even human social behavior, from which the intelligence is emerged [1–3]. SI provides a framework to explore distributed problem solving without centralized control or the provision of a global model. The particle swarm model helps to find optimal regions of complex search spaces through interaction of individuals in a population of particles [4]. It has exhibited good performance across a wide range of applications [5–11].

In the swarm dynamic system, the intelligence emerges from a chaotic balance between individuality and sociality. The chaotic balances are a characteristic feature of the complex system. Many studies on swarm intelligence have been presented and even some improved algorithms were proposed based on the chaotic search behavior. For a given energy or cost function, by following chaotic ergodic orbits [12], a chaotic dynamic system may eventually reach the global optimum or its good approximation with high probability. To enhance the performance of particle swarm optimization (one of the swarm intelligent models), Liu et al. [13] proposed hybrid particle swarm optimization algorithm by incorporating chaos. The proposed chaotic particle swarm optimization combined the population-based evolutionary searching ability of particle swarm optimization and chaotic search behavior. Simulation results and comparisons with the standard particle swarm optimization and several other meta-heuristics have shown that the approach could effectively enhance the search efficiency and greatly improve the searching quality. Since chaotic mapping possesses properties of certainty, ergodicity and stochastic property, Jiang and Etorre [14,15] introduced chaos mapping into the particle swarm optimization algorithm for reactive power optimization and short term hydroelectric system scheduling in a deregulated environment. Empirical results demonstrated that the performance of the algorithms

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1568-4946/$ – see front matter
doi:10.1016/j.asoc.2006.10.006

was improved obviously owing to its fast convergence and high precision.

However, not much work has been reported in the literature on the chaotic characteristics in swarm intelligence. In fact, several other studies in diverse fields indicated the analysis of the chaotic characteristics contributed to the understanding and applications of those complex systems. Chen [16] investigated the chaotic phenomena in macroeconomic systems, and offered an explanation of the multi-periodicity and irregularity in business cycles and of the low-dimensionality of chaotic monetary attractors. The empirical and theoretical results improved monetary control policy and the approaches to forecasting business cycles. Chialvo et al. [17] studied chaotic patterns of activation and action potential characteristics in the cardiac tissues. Their results indicated an apparent link between the mechanism of low dimensional chaos and the occurrence of reflected responses which could lead to more spatially disorganized phenomena. Frank et al. [18] analyzed the chaotic characteristics in the brain dynamics to predict changes of epileptic seizures. Goldberger et al. [19], Freeman [20] and Sarbadhikari and Chakrabarty [21] illustrated that chaos has a great important influence on brain and the evolutionary relationship between species. The investigations of chaotic dynamics in neural networks [22] promoted the development of neural networks and chaotic neural networks [23,24]. The chaotic balances and their characteristic in swarm intelligence has become very importance for its deeper understanding, application development and designing new computational models.

This paper investigates the chaotic dynamic characteristics in swarm intelligence, and analyzes their relationship with the performance of SI. Particle swarm model is investigated as a case study. The swarm intelligent model is represented as an iterated function system (IFS) [25]. We simulate and analyze the dynamic trajectory of the particle based on the IFS. The Lyapunov exponent and the correlation dimension are calculated and analyzed numerically for the dynamic system. The dependence of the parameters is discussed analytically using function optimization experiments.

The rest of the paper is organized as follows. Particle swarm model is presented in Section 2 and the concepts of iterative function system and its sensitivity is illustrated in Section 3. Dynamic chaotic characteristics are depicted and discussed in Section 4 and finally conclusions are made in Section 5.

2. Particle swarm model

A particle swarm model consists of a swarm of particles moving in a d-dimensional search space where the fitness f can be calculated as a certain quality measure. Each particle has a position represented by a position-vector $\vec{x}_i$ (i is the index of the particle), and a velocity represented by a velocity-vector $\vec{v}_i$. Each particle remembers its own best position so far in a vector $\vec{p}_i$, and its jth dimensional value is $p_{i,j}$. The best position from the swarm thus far is then stored in a vector $\vec{p}_g$, and its jth dimensional value is $p_{g,j}$. During the iteration time t, the update of the velocity from the previous velocity is determined by (1). Subsequently, the new position is determined by the sum of the previous position and the new velocity by (2):

$$v_{i,j}(t) = wv_{i,j}(t-1) + c_1 r_1 (p_{i,j}(t-1) - x_{i,j}(t-1)) + c_2 r_2 (p_{g,j}(t-1) - x_{i,j}(t-1)) \quad (1)$$

$$x_{i,j}(t) = x_{i,j}(t-1) + v_{i,j}(t) \quad (2)$$

where r_1 and r_2 are the random numbers, uniformly distributed within the interval [0, 1] for the jth dimension of ith particle. c_1 is a positive constant termed as the coefficient of the self-recognition component; c_2 is a positive constant termed as the coefficient of the social component. The variable w is the inertia factor, for which value is typically setup to vary linearly from 1 to 0 during the iterated processing. From (1), a particle decides where to move next, considering its own experience, which is the memory of its best past position, and the experience of its most successful particle in the swarm. In the particle swarm model, the particle searches the solutions in the problem space within a range $[-s, s]$ (if the range is not symmetrical, it can be translated to the corresponding symmetrical range). In order to guide the particles effectively in the search space, the maximum moving distance during one iteration is clamped in between the maximum velocity $[-v_{\max}, v_{\max}]$ given in (3), and similarly for its moving range given in (4):

$$v_{i,j} = \mathrm{sign}(v_{i,j})\min(|v_{i,j}|, v_{\max}) \quad (3)$$

$$x_{i,j} = \mathrm{sign}(x_{i,j})\min(|x_{i,j}|, x_{\max}) \quad (4)$$

The value of $v_{\max}$ is $\rho \times s$, with $0.1 \leq \rho \leq 1.0$ and is usually chosen to be s, i.e. $\rho = 1$. The pseudo-code for particle-search is illustrated in Algorithm 1.

Algorithm 1. Particle swarm model

Initialize the size of the particle swarm n, and other parameters.
Initialize the positions and the velocities for all the particles randomly.
While (the end criterion is not met) do
    $t = t + 1$;
    Calculate the fitness value of each particle;
    $\vec{p}_g(t) = \mathrm{argmin}_{i=1}^{n}(f(\vec{p}_g(t-1)), f(\vec{x}_1(t)), f(\vec{x}_2(t)), \ldots, f(\vec{x}_i(t)), \ldots, f(\vec{x}_n(t)))$
    For $i = 1$ to n
        $\vec{p}_i(t) = \mathrm{argmin}_{i=1}^{n}(f(\vec{p}_i(t-1))), f(\vec{x}_i(t))$;
        For $j = 1$ to d
            Update the jth dimension value of $\vec{x}_i$ and $\vec{v}_i$ according to (1), (3), (2), (4);
        Next j
    Next i
End While.

3. Iterated function system and its sensitivity

Clerc and Kennedy have stripped the particle swarm model down to a most simple form [26]. If the self-recognition