Adaptive Particle Swarm Optimizer with Nonextensive Schedule

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ABSTRACT
This paper introduces a class of adaptive particle swarm optimization (PSO) methods that build on the theory of nonextensive statistical mechanics. These methods combine the traditional position update rule with an annealing schedule that is based on the nonextensive entropy. Comparative experiments conducted on benchmark functions, have showed that the tested algorithms outperform the standard PSO.

Categories and Subject Descriptors
I.2.m Computing Methodologies, ARTIFICIAL INTELLIGENCE, Miscellaneous

General Terms
Algorithms.

Keywords
Global Search, Nonextensive Statistical Mechanics, Particle Swarm Optimizer, Swarm Intelligence.

1. INTRODUCTION
The Particle Swarm Optimization (PSO) algorithm is a population-based evolutionary computation technique for global optimization [1]. Studies and comparisons between PSO and the standard GA [2], showed that PSO may exhibit problematic behavior when it reaches a near optimal solution in several real-valued function optimization problems. Many variants of PSO have been proposed so far following Eberhart and Kennedy's work in this area [2]. In this work, new variants of the PSO algorithm are proposed based on nonextensive statistical mechanics[3].

2. THE NONEXTENSIVE PSO METHODS
Tsallis has defined the nonextensive entropy [3]:

$$S_q \equiv K \frac{1-\sum_{i=1}^{W} p_i^q}{q-1} \quad \left(q \in \mathbb{R}\right), \tag{1}$$

where W is the total number of microscopic configurations, whose probabilities are p_i^q, $K>1$ is a conventional constant and q is the entropic index. Optimization of Eq. (1) leads to the *q-exponential function*:

$$e_q^x \equiv \left[1+(1-q)x\right]^{\frac{1}{(1-q)}} \tag{2}$$

The first PSO variant incorporates stochasticity in search by adopting the following model:

$$Q_{(T,k)} = e_q^{-T(\ln 2)k} = \left[1+(1-q)T\left(\ln 2\right)k\right]^{\frac{1}{(1-q)}} \tag{3}$$

where T is the temperature and k indicates iterations. In this approach the velocity equation uses an inertia weight as in classical PSO and the particle's location is updated as follows:

$$x_{id}^{k+1} = x_{id}^{k} + Q_{i(T,k)} \upsilon_{id}^{k} = e_q^{-T(\ln 2)k} \tag{4}$$

where $Q_{i(T,k)}$ is defined by Eq. (3). By tuning q and T, the term $Q_{i(T,k)}$ provides an alternative to using a fixed constriction coefficient to control the velocity term.

The second PSO variant *Nonextensive Evolving PSO* uses a cooling procedure, defining a relationship between T and q. In this approach the term $Q_{(T,k)}$ is changing dynamically by the cooling procedure that is described by the next equation:

$$T = T_0\left(2^{q-1}-1\right)\left(\left(1+k\right)^{q-1}-1\right)^{-1}, \quad q>1 \tag{5}$$

where T_0 is the initial temperature.

3. REFERENCES
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