An Improved Quantum-behaved Particle Swarm Optimization Algorithm Based on Culture

Gao X. Z[2], Wu Ying[1], Huang Xianlin[1] and Kai Zenger[2],

[1] Center for Control Theory and Guidance Technology, Harbin Institute of Technology, 150001 Harbin, China
[2] Department of Automation and Systems Technology, Aalto University School of Electrical Engineering, 00076 Aalto, Finland
{ xiao-zhi.gao@aalto.fi, wying_hit@hotmail.com, xlinhuang@hit.edu.cn, kai.zenger@ aalto.fi, }

Abstract. An improved culture-based quantum-behaved particle swarm optimization algorithm (CQPSO) is proposed. The cultural framework is embedded in the QPSO, and the knowledge stored in the belief space can guide the evolution of the QPSO. 15 high-dimensional and multi-modal functions are employed to investigate the proposed algorithm. Numerical simulation results demonstrate that the CQPSO can indeed outperform the QPSO.

Keywords: Culture-based; Quantum-behaved; PSO; Knowledge.

1 Introduction

The Particle Swarm Optimization (PSO) is a population-based optimization method [1]. It might be stuck into local optima when dealing with multi-modal optimization problems. One of the novel hybridization for PSO is to apply the Quantum laws of mechanics to observe its behavior---Quantum-behaved PSO (QPSO), which has less parameters to control [2]. Cultural Algorithm (CA) proposed by Reynolds in 1995 is a powerful solution to demanding problems, due to its flexibility and efficiency [3].

In this paper, a novel cultural quantum-behaved Particle Swarm Optimization, CQPSO, is proposed to improve the convergence performance of the QPSO. The mutation operator and CA work together to increase the diversity of the swarm population, and enhance the global search capability of the QPSO.

2 Quantum-behaved Particle Swarm Optimization

Suppose there are N particles in the particle swarm, which are initialized randomly. Each particle can fly in the D-dimension search space according to its own velocity $V_i = (v_{i1}, v_{i2}, .. v_{iD})$. The particles are associated with their positions $X_i = (x_{i1}, x_{i2}, .. x_{iD})$ standing for the possible solutions to the problems under consideration. In the QPSO, all the particles have the quantum behavior. The state of a particle in QPSO is stated by wave function $\left|\psi\left(x,t\right)\right|^2$ [4]. The particles move according to the following formulations:

$$X_i^{t+1} = \begin{cases} M_i^t + belta*\left|X_{mbest}^t - X_i^t\right|*\ln(1/u) & if \;\; k \geq 0.5 \\ M_i^t - belta*\left|X_{mbest}^t - X_i^t\right|*\ln(1/u) & if \;\; k < 0.5 \end{cases}. \quad (1)$$

$$X_{mbest}^t = \frac{1}{N}\sum_{i=1}^{N} X_i^t, \;\; X_i^t = (x_{i1}^t, x_{i2}^t \cdots x_{iD}^t), \;\; M^t = \frac{c_1 * x^t + c_2 * Pg^t}{c_1 + c_2}. \quad (2)$$

where *belta* is the contraction-expansion coefficient, c_1、c_2、u and k are uniformly random numbers.

3 Cultural Quantum-behaved Particle Swarm Optimization

As proposed by Reynolds, the CA is composed of population space, belief space and the communication protocol [3]. The belief space is the place, where cultural knowledge is formed and stored. In this paper, two typical kinds of knowledge are used: situational knowledge, normative knowledge.

The combination of cultural algorithm and PSO can not guide the iteration for the velocity in a proper way. The emergency of the quantum-behaved particle swarm optimization can solve this problem, because the position is the only iteration term in the QPSO. In this paper, four kinds of influence functions are utilized to decide the iteration for the QPSO to improve the performance of the QPSO.

For example，if the normative knowledge and situational knowledge are used to determine the size of the mutation change and direction of the mutation respectively, our CQPSO is named as CQPSO (NsSd).

4 Simulation Results

A total of 15 nonlinear functions with 30 dimension are used to investigate the optimization capability of our CQPSO. The optimization results are provided in Table 1. It can be figured that the performance of the CQPSO is much better than that of the QPSO for almost all the functions except for the Sal function and Schwefel function.

Table 1. Function optimization performance comparison

Functions	PSO	CQPSO (NsSd)	CQPSO (NsNd)	CQPSO (Sd)	CQPSO (Ns)
Ackley	1.2436	0.8856	0.2310	1.1877×10^{-4}	0.5860
CM	-0.3453	-1.3899	-2.0098	-2.0676	-1.3456
DeJongf4	0.0246	4.5454×10^{-322}	6.5711×10^{-322}	9.4242×10^{-18}	1.9994×10^{-293}
Expfun	1.2266	1.0000	1.0000	1.0000	1.0000
Griewank	0.0190	1.2212×10^{-16}	6.6613×10^{-17}	1.1102×10^{-17}	1.8874×10^{-16}
Hyperellip	20.9658	7.4660×10^{-277}	1.4426×10^{-273}	6.4493	2.8919×10^{-225}
LM1	0.0962	1.5705×10^{-32}	1.5705×10^{-32}	1.5705×10^{-32}	1.5705×10^{-32}
LM2	1.6626	0.0099	0.0065	0.0011	0.0312
Neumaier	-133.3331	-4930	-4930	-4928.6	-4930
Rastrigin	57.2142	23.3815	22.6850	19.2635	23.8790
Rosenbrock	65.8476	1.1960	0.4036	28.3834	0.8098
Sal	0.2679	0.3199	0.3199	0.3199	0.3399
Schwefel	6462.2058	6791.9461	7.0318568	6312.3102	6514.5500
Schaffer	19.1880	19.0074	14.8900	19.6145	17.0914
Sphere	0.1425	4.0166×10^{-272}	5.6356×10^{-281}	1.4878×10^{-144}	1.2513×10^{-228}

Acknowledgments. This work is supported by the Academy of Finland under Grants No. 135225 and No. 127299 and the NSFC under Grant No. 60874084.

References

1. Eberhart, R., Kennedy, J.: A New Optimizer Using Particle Swarm Theory. In: 6th International Symposium on Micro Machine and Human Science. pp. 39-43, Nagoya (1995)
2. Jun, S., Bin F., Wenbo, X.: Particle Swarm Optmization with Particles Having Quantum Behavior. In: CEC2004. Congress on Evolutionary Computation. pp. 325-331, San Diego (2004)
3. Reynolds, R.G.:An Introduction to Cultural Algorithms. In: 3rd Annual Conference on Evolutionary Programming. pp. 131-139, SanDiego (1994)
4. Jing, L., Wenbo, X., Jun, S.: Quantum-behaved Particle Swarm Optimization with Mutation Operator. In: 17th IEEE International Conference on Tools with Artificial Intelligence, pp.237-240. IEEE Press, Hong Kong (2005)