Fitness Proportionate Selection Based Binary Particle Swarm Optimization

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ABSTRACT

Particle Swarm Optimization(PSO) has shown its advantages not only in dealing with continous optimization problems, but also in dealing with discrete optimization problems. Binary Particle Swarm Optimization(BPSO), the discrete version of PSO, has been widely applied to many areas. Although there are some variations aiming to improve BPSO's performance, none of them has been proven to be a promissing alternative. In this paper, we propose a novel binary particle swarm optimization called Fitness Proportionate Selection Based Binary Particle Swarm Optimization(FPSBPSO). We test FPSBPSO's performance in function optimization problems and multidimension knapsack problems. Experimental results show that FPSBPSO can find better optima than BPSO and a variation of BPSO.

Categories and Subject Descriptors

D.3.3 [**Programming Languages**]: Language Constructs and Features—*abstract data types, polymorphism*

General Terms

Algorithms, Performance, Reliability, Experimentation

Keywords

Particle Swarm Optimization, Discrete Optimization, Fitness Proportionate Selection

1. INTRODUCTION

Particle Swarm Optimization(PSO) [2] was originally designed to solve continous optimization problems. In order to deal with discrete problems, Kennedy and Eberhart proposed binary particle swarm optimization(BPSO) [3] in 1997. BPSO has attracted much attention, however, most researchers focused more on the application of BPSO rather

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than the analysis of BPSO. Although there are several improved versions of BPSO, none of them has become a real alternative to BPSO. The original BPSO model is used in most publications reporting the application of PSO in dealing with discrete problems.

There are severl problems with BPSO. Engelbrecht argue that maybe inertial weights is useless in BPSO [1]. Khanesar discussed the memory problem and parameter selection problem of BPSO in [4].

Our goal is to improve PSO's performance in dealing with discrete problems with a better interpretation than BPSO. A new way to calculate velocities based on fitness values is proposed and based on that we will propose a new binary version of PSO named FPSBPSO.

2. NEW METHOD

We adopt fitness proportionate selection to update a particle's position component, and that is why we call the new model FPSBPSO. In the following content, when we refer to involved particles in the folloing content, we actually mean the three particles p_i , p_i 's personal best particle p_i^{pb} and p_i 's global best particle p_i^{gb} . The newly designed update formulas are as follows.

$$v_{id}^{t+1} = \begin{cases} mr, & if \ n_0 == 0\\ 1 - mr, & if \ n_1 == 0\\ \frac{f_1}{f_1 + f_0}, & otherwise. \end{cases}$$
(1)

$$x_{id}^{t+1} = \begin{cases} 0, & rand < v_{id}^{t+1} \\ 1, & otherwise. \end{cases}$$
(2)

Where n_0 is the number of involved particles with $x_{id} = 0$, while n_1 is the number of involved particles with $x_{id} = 1$. f_1 and f_0 are computed as follows: First, involved particles are divided into two sets S_1 and S_0 based on whether they select 1 or 0 at the d_{th} bit. Then, f_1 and f_0 are calculated by averaging the fitness values of particles in S_1 and S_0 respectively. v_{id}^{t+1} is the probability of setting x_{id}^{t+1} to 0. The higher f_1 is, the higher probability x_{id}^{t+1} will be 0. It is obvious that the formulas given above are for minimization problems and can easily be modified to deal with maximization problems.

In this new model, the update formula for velocities is very different from that of the BPSO. Parameters commonly used in PSO models like inertial weight and V_{max} are eliminated. A new parameter mr is added and it is the only one free parameter.

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Table 1: Dimension=5									
		Average	Э		Best			Std	
	BPSO	NBPSO	FPSBPSO	BPSO	NBPSO	FPSBPSO	BPSO	NBPSO	FPSBPSO
Ackley	5.10	$4.00 * 10^{-03}$	$1.82 * 10^{-10}$	2.73	$1.00 * 10^{-3}$	$1.80 * 10^{-10}$	1.01	0.00	0.00
Griewank	0.17	0.02	0.02	0.07	$0.66 * 10^{-06}$	0.0	0.05	0.01	0.01
Rastrigin Rosenbrock	$36.22 \\ 816.46$	0.40 28.04	0.13 52.56	$15.8 \\ 39.65$	$0.22 * 10^{-03}$ 0.67	0.0 1.35	$9.07 \\ 641.61$	$0.60 \\ 104.39$	$0.35 \\ 138.77$
Sphere	5.10	$0.80 * 10^{-5}$	$1.00 * 10^{-20}$	0.51	$0.10 * 10^{-06}$	$1.00 * 10^{-20}$	2.93	$1.39 * 10^{-5}$	0.00
Shifted Weierstrass	2.32	0.26	0.13	0.97	0.10	$0.90 * 10^{-04}$	0.38	0.13	0.10

Table 2: Dimension=10										
		Averag	e	Best			Std			
	BPSO	NBPSO	FPSBPSO	BPSO	NBPSO	FPSBPSO	BPSO	NBPSO	FPSBPSO	
Ackley	15.65	1.57	$4.82 * 10^{-07}$	12.78	0.55	$3.91 * 10^{-08}$	1.03	0.47	$6.78 * 10^{-7}$	
Griewank	1.03	0.18	0.09	0.76	0.07	$4.44 * 10^{-16}$	0.08	0.07	0.05	
Rastrigin	41.04	27.78	3.97	190.63	12.40	$2.52 * 10^{-11}$	105.66	6.96	2.67	
Rosenbrock	$1.74 * 10^{6}$	259.52	133.17	$1.44 * 10^5$	20.77	5.74	$9.48 * 10^5$	461.81	416.69	
Sphere Shifted Weierstrass	359.03 8.83	$0.35 \\ 4.06$	$5.84 * 10^{-13}$ 0.55	$ \begin{array}{r} 149.28 \\ 6.48 \end{array} $	$0.09 \\ 2.24$	$1.67 * 10^{-16}$ 0.03	$ \begin{array}{r} 103.55 \\ 0.67 \end{array} $	$0.19 \\ 0.80$	$3.66 * 10^{-12}$ 0.26	

Table 3: Dimension=20										
	Average				Best			Std		
	BPSO	NBPSO	FPSBPSO	BPSO	NBPSO	FPSBPSO	BPSO	NBPSO	FPSBPSO	
Ackley	20.14	8.25	$5 * 10^{-03}$	18.02	10.35	$0.16 * 10^{-02}$	0.37	1.38	0.00	
Griewank Rastrigin	$\frac{1.81}{3556.82}$	$\frac{1.03}{218.04}$	$0.060 \\ 11.17$	$ \begin{array}{r} 1.50 \\ 1852.17 \end{array} $	$0.99 \\ 313.40$	$5.16 * 10^{-07}$ 32.86	$0.11 \\ 464.50$	$ \begin{array}{c} 0.01 \\ 48.06 \end{array} $	$0.05 \\ 9.06$	
Rosenbrock	$1.17 * 10^8$	$5 * 10^{5}$	570.64	$4.18 * 10^{7}$	$7.37 * 10^4$	16.31	$2.99 * 10^{7}$	$3.78 * 10^{5}$	1141.85	
Sphere Shifted Weierstrass	$3335.40 \\ 23.79$	$133.12 \\ 17.68$	$2.15 * 10^{-05}$ 2.70	$2275.78 \\ 20.30$	$57.43 \\ 14.00$	$1.65 * 10^{-06}$ 1.13	$426.08 \\ 0.98$	$42.88 \\ 1.43$	$2.32 * 10^{-5}$ 0.77	

			Ta	ble 4: Di	mension=	=30			
		Average			Best		Std		
	BPSO	NBPSO	FPSBPSO	BPSO	NBPSO	FPSBPSO	BPSO	NBPSO	FPSBPSO
Ackley	20.82	17.23	0.41	20.19	14.39	0.10	0.10	1.35	1.43
Griewank Rastrigin	$2.88 \\ 8004.77$	$1.30 \\ 1493.37$	$0.03 \\ 69.88$	$2.52 \\ 5796.02$	$\substack{1.14\\646.46}$	$6.67 * 10^{-04}$ 22.34	$0.18 \\ 671.97$	$0.08 \\ 280.06$	$0.03 \\ 16.96$
Rosenbrock	$4.56 * 10^8$	$2.66 * 10^{7}$	707.43	$2.42 * 10^8$	$8.50 * 10^{06}$	30.61	$8.47 * 10^{7}$	$1.05 * 10^{7}$	1045.43
Sphere Shifted Weierstrass	$7573.83 \\ 40.19$	$1225.85 \\ 33.15$	$0.02 \\ 6.80$	$4606.81 \\ 34.37$		$4*10^{-03}$ 4.48	$850.31 \\ 1.27$	$320.48 \\ 1.84$	$ \begin{array}{c} 0.02 \\ 1.23 \end{array} $

Table	5:	Student	T-test	Results
		$i_{m} = 10$		$D_{im} = 00$

	Dim=5		Dim=10		Dim	=20	Dim=30	
	BPSO	NBPSO	BPSO	NBPSO	BPSO	NBPSO	BPSO	NBPSO
Ackley	$1.56 * 10^{-72}$	$1.40 * 10^{-35}$	$2.35 * 10^{-119}$	$1.59 * 10^{-56}$	$3.72 * 10^{-174}$	$5.86 * 10^{-89}$	$4.59 * 10^{-117}$	$1.35 * 10^{-158}$
Griewank	$2.80 * 10^{-54}$	0.87	$4.26 * 10^{-144}$	$6.11 * 10^{-25}$	$4.85 * 10^{-151}$	$1.39 * 10^{-153}$	$1.41 * 10^{-126}$	$2.27 * 10^{-144}$
Rastrigin	$8.27 * 10^{-63}$	$0.10 * 10^{-2}$	$4.89 * 10^{-67}$	$9.83 * 10^{-63}$	$1.43 * 10^{-89}$	$1.19 * 10^{-81}$	$1.97 * 10^{-108}$	$4.89 * 10^{-73}$
Rosenbrock	$8.64 * 10^{-21}$	0.16	$1.12 * 10^{-33}$	0.04	$3.62 * 10^{-62}$	$1.29 * 10^{-24}$	$3.64 * 10^{-75}$	$6.97 * 10^{-45}$
Sphere	$6.33 * 10^{-32}$	$4.37 * 10^{-9}$	$3.51 * 10^{-57}$	$2.21 * 10^{-34}$	$7.48 * 10^{-91}$	$7.88 * 10^{-53}$	$2.51 * 10^{-96}$	$4.10 * 10^{-61}$
Shifted Weierstrass	$3.54 * 10^{-84}$	$4.02 * 10^{-15}$	$3.20 * 10^{-132}$	$4.80 * 10^{-73}$	$7.58 * 10^{-207}$	$3.05 * 10^{-135}$	$3.50 * 10^{-225}$	$1.28 * 10^{-167}$

3. EXPERIMENTS

In order to evaluate FPSBPSO's performance, we tested FPSBPSO on two kinds of problems: function optimization problem and Multidimension knapsack problem(MKP). We compare FPSBPSO's results with the basic BPSO's results and NBPSO's results [4]. The fitness function we used in MKP was proposed by Khuri et al. in [5].

Experimental results are shown in six tables. From Table 1 to Table 5 are results obtained on function optimization problems while Table 7 gives results on MKP. Table 6 gives the MKP description.

Table 6: MKP Benchmark										
	n m	Best K	nown		n	m	Best	Known		
$^{1}_{2}_{3}_{4}$		$egin{array}{cccc} 0 & 3800 \ 0 & 8706.1 \ 0 & 4015 \ 0 & 6120 \end{array}$		5 6 7	$28 \\ 39 \\ 50$	555	12400 10618 1653) 3 7		
	Table 7: MKP Results									
	В	PSO	NE	SP:	50		FPSE	<u>spso</u>		
	Best	Avg.	Best	F	Avg.		est	Avg.		
$ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \end{array} $	$\begin{array}{r} 3800 \\ 8706.1 \\ 4015 \\ 6120 \\ 12380 \\ 10490 \\ 16217 \end{array}$	$3800 \\ 8706.1 \\ 4014.5 \\ 6107.5 \\ 12298.5 \\ 10431.3 \\ 16150.55$	$3800 \\ 8706.1 \\ 4015 \\ 6120 \\ 12400 \\ 10618 \\ 16519$	3 8 4 6 1 1 1	$800 \\ 632.26 \\ 014.5 \\ 114.5 \\ 2387 \\ 0560.2 \\ 6430$	38 87 40 61 12 5 10 16	00 06.1 15 20 400 618 537	3800 8706.1 4014.5 6117.5 12386.5 10564 16481		

4. CONCLUSIONS

In this paper, we redefined the velocity component and proposed a new BPSO model. The new model is very simple with only one free parameter. Experimental results show that the new model is superior to BPSO, especially when the dimensionality of the optimization problem is high.

5. ACKNOWLEDGMENTS

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