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Intelligent Particle Swarm Optimization

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Abstract*— This paper Intelligent Particle Swarm Optimization (IPSO) to optimize difficult multimodal optimization problems with fast convergence. In Intelligent Particle Swarm Optimization (IPSO), the positions of particle are updated by pbest (Personal or local best) and gbest (Global best) global best particle positions. The main advantages of IPSO are that it doesn't require velocity equation. In addition, it does not require any additional parameter like acceleration coefficients and inertia weight as the case in other PSO algorithms. During the initial stages of the experimentation, the step size will be large and during the final stage of the experimentation, the step size is reduced to smaller value. The IPSO technique is tested with three benchmark functions and results are compared with variants of PSO. The results of benchmark functions validate that the proposed technique is more efficient for improving the quality of global optima with less computational requirement.

Key Words: **Intelligent Particle Swarm Optimization (IPSO), pbest (Personal or local best) and gbest, (Global best) global best.**

I. INTRODUCTION

Soft computing techniques like evolutionary algorithms, bio-inspired algorithms, metaheuristics algorithms, artificial neural networks and Fuzzy Logic are extensively used in engineering, science and allied fields to analyze complex phenomena for which conventional methods are not suitable or difficult to use. In the optimization problem, soft computing plays important roles. The capability to find a global optimum, without being trapped in local optima, and the possibility to well face nonlinear and discontinuous problems, with great numbers of variables, are some advantages of these techniques. These methods avoid the need to compute any derivatives.

Since 1960's Genetic Algorithm (GA) has proved its dominant role in the optimization world [1-2]. The Particle Swarm Optimization (PSO) is a population-based optimization method developed by Eberhart and Kennedy in 1995 [3]. It is inspired by social behavior of bird flocking or fish schooling. It can efficiently handle problems like nonlinear, unimodal and multimodal function optimizations [4].

The new variants of PSO are proposed for faster convergence and better quality of optimum solution like Supervisor-Student Model in Particle Swarm Optimization (SSM-PSO) [5], Linear Decreasing Weight Particle Swarm Optimization (LDW-PSO) [6], Gregarious Particle Swarm Optimization (GPSO) [7], Global and Local Best Particle Swarm Optimization (GLBestPSO)[8] and Emotional Particle Swarm Optimization (EPSO)[9]. The authors propose Intelligent Particle Swarm Optimization (IPSO). The rest of the paper is organized in four fold. The section 2 depicts the review of original Particle Swarm Optimization (PSO). The section 3 depicts the proposed method. In section 4, experimental results on benchmark functions by proposed method and other published techniques are presented. Section 5 comprises of conclusion.

II. REVIEW OF PARTICLE SWARM OPTIMIZATION

The original framework of PSO is designed by Kennedy and Eberhart in 1995. There fore, it is known as standard PSO [3].

PSO follows the optimization process by means of personal or local best (p_i), global best (p_g), particle position or displacement (X) and particle velocity (V). For each particle, at the current time step, a record is kept for the position, velocity, and the best position found in the search space. Each particle memorizes its previous velocity and the previous best position and uses them in its movements [3]. The velocities (V) of the particles are limited in [Vmin Vmax]^D. If V is smaller than Vmin then V is set to Vmin or Xmin**.** If V greater than Vmax then V is set to Vmax or Xmax**.** Since the original version of PSO lacks velocity control mechanism, it has a poor ability to search at a fine grain.

The two updating fundamental equations in a PSO are velocity and position equations, which are expressed as Eq. (1) and (2).

$$V_{id}(t+1) = V_{id}(t) + c_1 * r_{1d}(t) * (p_{id}(t) - X_{id}(t)) + c_2 * r_{2d}(t) * (p_{gd}(t) - X_{id}(t))$$

$$c_2 * r_{2d}(t) * (p_{gd}(t) - X_{id}(t)) \quad \text{.... (1)}$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \quad \text{..... (2)}$$

Where,

t= Current iteration or generation.

i = Particle Number.

d= Dimensions.

$V_{id}(t)$ = Velocity of i-th particle for d-dimension at iteration t .

$X(t)$ = Position of i-th particle for d-dimension at iteration t.

c_1 and c_2= Acceleration constants.

$r_{1d}(t)$ and $r_{2d}(t)$ = Random values [0 1] for d- dimension at iteration t.

$p_{id}(t)$= Personal or local best of i-th particle for d-dimension at iteration t.

$p_{gd}(t)$ = Global best for d-dimension at iteration t.

The right side of Eq. (1) consists of three parts. The first part of equation is the previous velocity of the particle. The second part is the cognition (self-knowledge) or memory, which represents that the particle is attracted by its own previous best position and moving toward to it. The third part is the social (social knowledge) or cooperation, which represents that the particle is attracted by the best position so far in population and moving towards to it. There are

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restrictions among these three parts and can be used to determine the major performance of the algorithm.

III. INTELLIGENT PARTICLE SWARM OPTIMIZATION

In IPSO, the positions of particle are updated by *pbest* (Personal or local best) and *gbest* (Global best) global best particle positions as expressed in Eq. (3). The main advantages of IPSO are that it doesn't require velocity equation. In addition, it does not require any additional parameter like acceleration coefficients and inertia weight as the case in other PSO algorithms.

$$X_i(t+1)=((gbest\text{-}pbesi_t/Xi(t)) * r_1 + (1\text{-}gbest/pbesi_t) * r_2 \qquad ......(3)$$

Where,
t= Current iteration or generation.
i = Particle Number.
r_1 and r_2 = Random values [0 1] at iteration t.
$pbesi_t$ = Personal or local best of i-th particle at iteration t.
$gbest$ = Global best at iteration t.

During the initial stages of the experimentation, the step size will be large and thus the positions of particles are away from the global best position. During the final stage of the experimentation, the step size is reduced to smaller value.

IV. EXPERIMENTAL RESULTS FOR BENCHMARK FUNCTIONS

The well-known ten benchmark functions [5] in Table I are used to validate performance of the proposed technique (IPSO). The authors are considered both unimodal and multimodal functions to test efficiency of the IPSO. For this, the functions f_1 are taken for unimodal verification and f_2 to f_3 meant for multimodal. The global optima, search range and initialization range for each benchmark function is presented in Table II [5]. The stopping criteria of the proposed method is same as compared method.

The IPSO has been tested on Rosenbrock, Rastrigin and Griewank benchmark functions by changing dimensions(d), generations(T) ,population size (P) with 30 trials as shown in Table III, IV4 and V The results are compared with SSM-PSO [5] and LDW-PSO[5]. The low values of fitness obtained by IPSO validate that , the proposed technique outperforms well than SSM-PSO [5] and LDW-PSO [5] for Rosenbrock, Rastrigin and Griewank benchmark functions. As seen from results the IPSO improves the quality of optima as the number generation progresses. The presented method is suitable for optimization of unimodal and multimodal functions.

Table I: Benchmark Functions for simulations, where *d* is the dimension of the function

Function Name	Mathematical Description
Rosenbrock f_1	$\sum_{i=1}^{d}(100(x_{i+1}-x_i^2)^2+(x_i-1)^2$
Rastrigin f_2	$\sum_{i=1}^{d}(x_i^2-10COS\,2\pi x_i+10)$
Griewank f_3	$\frac{1}{4000}\sum_{i=1}^{d}x_i^2-\prod_{i=1}^{d}COS\frac{x_i}{\sqrt{i}}+1$

Table II: Search range and initialization range for the benchmark functions

Function	Global Optima	Search Range	Initialization Range
Rosenbrock	0	$[-100, 100]^d$	$[15, 30]^d$
Rastrigin	0	$[-10, 10]^d$	$[2.56, 5.12]^d$
Griewank	0	$[-600, 600]^d$	$[300, 600]^d$

Table III: Mean Fitness Values for the Rosenbrock Function

Popul-ation	Dime-nsions	Itera-tions	SSM-PSO[5]	LDW-PSO[5]	IPSO
20	10	1000	80.6875	95.1724	**26.3439**
	20	1500	112.9138	205.3715	**44.8525**
	30	2000	247.4600	307.4165	**58.3225**
40	10	1000	30.0598	68.1148	**24.5682**
	20	1500	74.8393	175.9682	**41.5540**
	30	2000	133.9569	296.6071	**60.6644**
80	10	1000	11.4541	37.1952	**25.4656**
	20	1500	36.0802	85.1608	**41.3665**
	30	2000	56.5048	200.4575	**49.6875**

Table IV: Mean Fitness Values for Rastrigin Function

Popul-ation	Dime-nsions	Itera-tions	SSM-PSO[5]	LDW-PSO[5]	IPSO
20	10	1000	5.2552	5.6157	**0.2378**
	20	1500	21.3847	22.7886	**0.9542**
	30	2000	42.8655	47.1194	**5.5536**
40	10	1000	4.5459	3.6521	**0.6547**
	20	1500	18.6144	17.1412	**0.9669**
	30	2000	35.6870	38.6152	**26936**
80	10	1000	3.5159	2.4185	**0.5657**
	20	1500	12.2380	13.4634	**0.8345**
	30	2000	32.2035	30.3164	**3.4643**

Table 5: Mean Fitness Values for the Griewank Function

Popul-ation	Dime-nsions	Itera-tions	SSM-PSO[5]	LDW-PSO[5]	IPSO
20	10	1000	0.1178	0.0919	**0.00543**
	20	1500	0.0267	0.0302	**0.00789**
	30	2000	0.0416	0.0179	**0.00284**
40	10	1000	0.0923	0.0861	**0.00535**
	20	1500	0.0302	0.0292	**0.00267**
	30	2000	0.0168	0.0127	**0.00143**
80	10	1000	0.0753	0.0772	**0.00085**
	20	1500	0.0272	0.0280	**0.00056**
	30	2000	0.0179	0.0301	**0.00021**

V. CONCLUSION

The authors introduced Intelligent Particle Swarm Optimization (IPSO) to optimize difficult multimodal optimization problems with fast convergence. In Intelligent Particle Swarm Optimization (IPSO), the positions of particle are updated by pbest (Personal or local best) and gbest

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(Global best) global best particle positions. The main advantage of IPSO is that it doesn't require velocity equation. In addition, it does not require any additional parameter like acceleration coefficients and inertia weight as the case in other PSO algorithms. The results of benchmark functions obtained by IPSO validate that the proposed technique is more efficient for improving the quality of global optima of multimodal functions with less computational requirement.

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