An Evolutionary SPDE Breeding-Based Hybrid Particle Swarm Optimizer: Application in Coordination of Robot Ants for Camera Coverage Area Optimization

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Abstract. In this paper we propose a new Hybrid Particle Swarm Optimizer model based on particle swarm, with breeding concepts from novel evolutionary algorithms. The hybrid PSO combines traditional velocity and position update rules of RANDIW-PSO and ideas from Self Adaptive Pareto Differential Evolution Algorithm (SPDE). The hybrid model is tested and compared with some high quality PSO models like the RANDIW-PSO and TVIW-PSO. The results indicate two good prospects of our proposed hybrid PSO model: potential to achieve faster convergence as well as potential to find a better solution. The hybrid PSO model, with the abovementioned features, is then efficiently utilized to coordinate robot ants in order to help them to probe as much camera coverage area of some planetary surface or working field as possible with minimum common area coverage.

1 Introduction

Particle Swarm Optimization (PSO) is a population based self-adaptive search optimization technique, first introduced by Kennedy and Eberhart [1] in 1995. One of the latest promising quality models in PSO technique is the Particle Swarm Optimizer with Random Inertia Weight (RANDIW-PSO model). Evolutionary algorithms [5] are a kind of global optimization techniques that use selection and recombination as their primary operators to tackle optimization problems. *Differential evolution* (DE) is a branch of evolutionary algorithms developed by Rainer Storn and Kenneth Price for optimization problems over continuous domains. Of the latest Pareto Differential Evolution (PDE) algorithms, the Self-Adaptive Pareto Differential Evolution Algorithm (SPDE) [6] has the important property to self adapt the crossover and mutation rates.

The proposed hybrid PSO model incorporates crossover which is motivated by SPDE evolution. Here for some randomly selected dimensions particles are reselected and refined from SPDE crossover pool and goes under position updating. The paper is organized as follows: section 2 presents proposed hybrid PSO model, results and comparisons with some other PSO models are exhibited in section 3 and finally the

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hybrid PSO model is applied to solve coordination problem of robot ants which are engaged in covering some planetary surface by their camera, such that the common area coverage is minimum.

2 New Hybrid PSO Model

Here we propose a Hybrid Random Inertia Weight (RANDIW)-PSO model, in which breeding is performed by the Self Adaptive Pareto Differential Evolution (SPDE). The total algorithm is illustrated as follows:

A. Randomly generate the initial population.
B. Repeat
until number of generation reaches its maximum limit:
1. Randomly generate m number of dimensions that will be bred.
2. For i =1 to m, do
   a. Construct SPDE breeding pools, each of which contain position values of i-th dimension (x_i) of three particles, chosen randomly.
   b. In each of the breeding pools, do
      i. Mark the minimum of three x_i values as the main parent α_1. Other two are supporting parent α_2 and α_3.
      ii. The crossover rate of each individual is chosen as ($1-x_{ij}^{/}$), where $x_{ij}^{/}$ is the normalized position value of i-th dimension of j-th particle.
      iii. Calculate Crossover rate (x_c) of child:

$$x_c^{child} \leftarrow x_c^{\alpha 1} + r1 \cdot (x_c^{\alpha 2} - x_c^{\alpha 3}). \tag{1}$$

Where r1 is a random number [0, 1].

      iv. Crossover: Select a random variable j [1, 3]
For each variable k (value 1 or 2 or 3)
With some random probability [0, 1] > x_c^{child} or if $k = j$,
do
Crossover between that α_k and the main parent α_1.

Crossover is performed by arithmetic crossover on the position of the parents as follows:

$$child_1(x_i)=p_i.parent_1(x_i)+ (1.0-p_i).parent_2(x_i). \tag{2}$$

$$child_2(x_i)=p_i.parent_2(x_i)+ (1.0-p_i).parent_1(x_i). \tag{3}$$

Where p_i is uniformly distributed random value between 0 and 1. The velocity of the offspring is calculated as the sum of velocity vectors of the parent normalized to the original length of each parent velocity vector.

$$child_1(v)=[\{parent_1(v)+ parent_2(v)\}/ |parent_1(v)+ parent_2(v)|].|parent_1(v)|. \tag{4}$$

$$child_2(v)=[\{parent_1(v)+ parent_2(v)\}/ |parent_1(v)+ parent_2(v)|].|parent_2(v)|. \tag{5}$$

The arithmetic crossover of positions and velocity vectors used were empirically tested to be the most promising. The arithmetic crossover of positions in the search space is one of the most commonly used crossover methods with standard real valued GAs, placing the offspring within the hypercube spanned by the parent particles.

iv. After the crossover, from the three parent and children, three minimum individuals are retained.

3. Apply PSO equation: The PSO equation follows the TVIW-PSO model:

$$v_i = w.\ v_i + \varphi_{1i}.(p_i - x_i) + \varphi_{2i}.(p_g - x_i)\ . \tag{6}$$

$$x_i = x_i + v_i\ . \tag{7}$$

Where the inertia weight *w* is set to change randomly according to the following equation:

$$w = 0.5 + \{rand(.)/2\}\ . \tag{8}$$

The term rand(.) is a uniformly distributed random number within the range [0,1], thus with mean value 0.75. φ_{1i} and φ_{2i} are random values different for each particle and for each dimension. If the velocity is higher than a certain limit, called v_{max}, this limit will be used as the new velocity for this particle in this dimension, thus keeping the particles within search space.

3 Experimental Results

Our proposed SPDE breeding based hybrid RANDIW-PSO was compared with basic RANDIW-PSO and TVIW-PSO models on five standard test functions and it exhibited two important striking features of proposed hybrid PSO: faster convergence and resulting better solution, as illustrated clearly by the following tables and graphs.

Table 1. Initialization range, dynamic range and maximum for benchmarks

Test function	Range of search	Range of initialization	v_{max}
Sphere (f1)	$(-100,100)^n$	$(50,100)^n$	100
Rosenbrock (f2)	$(-100,100)^n$	$(15,30)^n$	100
Rastrigrin (f3)	$(-10,10)^n$	$(2.56,5.12)^n$	10
Griewank (f4)	$(-600,600)^n$	$(300,600)^n$	600
Schaffer (f6)	$(-100,100)^2$	$(15,30)^2$	100

Table 2. Average value of the benchmarks for 50 trials

Function	Dimension	Generation	Average		
			PSO-RANDIW	PSO-TVIW	Proposed SPDE based hybrid PSO
f1	10	1000	0.01	0.01	0.01
	20	2000	0.01	0.01	0.01
	30	3000	0.01	0.01	0.01
f2	10	3000	2.212	26.840	2.002
	20	4000	28.332	53.653	26.708
	30	5000	38.227	63.352	36.586
f3	10	3000	1.001	1.989	1.989
	20	4000	19.984	3.979	8.944
	30	5000	44.772	15.919	10.823
f4	10	3000	0.0372	0.0765	0.0276
	20	4000	0.0074	0.0812	0.0070
	30	5000	0.0932	0.1048	0.01478
f6	2	100	0.00247	0.00246	0.00240

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