Optimization Approach for Computational Intelligence based on Hybrid PSO and DE

Preeti Soni[1], Minu Choudhary[2]

[1]M. Tech Scholar, Software Engineering, RCET Bhilai, Chhattisgarh, India

[2]Associate Professor, Department of Information & Technology, RCET Bhilai, Chhattisgarh, India

Abstract: ***In this paper, combination of PSO and DE is proposed for quickly finding the global optimization solutions. The mutli-benchmark functions are used to test the performance of the proposed method. Empirical studies show that the proposed method helps in improving the union rate of the basic DE algorithm without compromising with the quality of solution. The main purpose of this cram work is to nearby the major techniques for quickly verdict the global solutions.***

Keywords: Particle Swarm Optimization, Differential Evolution, Global Solution, Hybridization**.**

1. Introduction

The standard PSO has difficulty with every time converging to large-scale optima, especially for multi-modal, high-dimensional functions. The aim of optimization is to determine the best-suited solution to a problem under given set of unconstraint. The global optimization of multi benchmark functions is an important topic in scientific and engineering investigates since many real situations can be modeled as nonlinear optimization problems. However, these PSO variants still have problems finding global solutions for some benchmark functions, high-dimensional functions. The goal of this paper is to combine PSO techniques with differential evolution algorithm for finding globally optimal solutions of high-dimensional functions. We will focus on whether our proposed new approach can find the global solutions for these functions, and examine the performance of these approaches in converge to a worldwide solution.

In computer science, differential evolution (DE) is a method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. Such methods are commonly known as meta heuristics as they make few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, meta heuristics such as DE do not guarantee an optimal solution is ever found.

2. Literature Survey

In **[1]** two hybrid PSO algorithms: one uses a Differential Evolution (DE) operator to replace the standard PSO method for updating a particle's position. The goal of this was to investigate hybrid PSO approaches to optimize multi-modal functions. The goal was successfully achieved by using a DE operator and integrating a local search. In both hybrid algorithms, the convergence to local optima was successfully avoided; two hybrid PSO algorithms were developed in this HybridPSO1 replaces the method in standard PSO with one DE operator and uses it to update particles. HybridPSO2 integrates one local search operator based on HybridPSO1, explores the local optimal position in particles region. Both hybrid PSO algorithms are effective to find the global solutions of the seven benchmark multi-modal and high-dimensional functions. Global Search and optimization problems are ubiquitous through the various realms of science and engineering as in **[2]**. This has provided a comprehensive overview of two promising optimization algorithms, which are currently gaining popularity for their greater accuracy, faster convergence speed and simplicity. One of these algorithms, known as PSO mimics the behaviour of a group of social insects in multi-agent cooperative search problems. The latter one called DE (DE) is a deviant variety of GA, which attempts to replace the crossover operator in GA by a special type of differential operator for reproducing offspring in the next generation.

In [3], a competitive variant of Differential Evolution with Local Search algorithm is proposed to address real world optimization problems. These optimization problems are very hard to optimize due to large number of local minima. So, a distant search method is also included to farther ensure that any subpopulation does not get trapped in some local optima. We have also developed a hybrid mutation strategy to overcome the fast but less reliable convergence. **[4]**, presents a hybrid particle swarm with differential evolution operator called DEPSO. The Hybrid strategy provides the bell-shaped mutations with consensus on the population diversity by DE operator, while keeps the self-organized particle swarm dynamics, in order to make the performance is not very sensitive to the choice of the strategy parameters. It is shown to outperform the PSO and DE for a set of benchmark functions. However, more comparative works with different parameter settings for more problems should be performed to provide a full view.

In [5], a new self-adaptive DE variant, SaNSDE, which is an improved version of our previous algorithm NSDE. The SaNSDE can be viewed as a hybridization of SaDE [2] and NSDE [1]. In SaNSDE: 1) It utilized the self-adaptation strategy of SaDE to adapt between candidate mutations; 2) It applied a self-adaptation to adjust parameter F; 3) Then it illustrated the ill-condition of original CR self-adaptation in SaDE, and proposed an enhanced version with weighting.

3. Methodology

In this paper, we use combining of different two algorithms to create a hybrid. In this two algorithms are used for hybridization, and they are: PSO (Particle Swarm Optimization) Differential evolutionary. The aim of optimization is to establish the best-suited elucidation to a problem under given set of constraints. Particle Swarm Optimization (PSO) is a stochastic global optimization method which originated from the recreation of the social behavior of birds within a congregate, as developed by Kennedy and Eberhart in 1995. In computer science, differential evolution (DE) is a method that optimizes a problem by iteratively trying to improve a contestant solution with regard to a given measure of quality.

3.1 Particle Swarm Optimization

PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. PSO maintains a population of candidate solutions (called particles) and moves these particles around the search space. Each particle "flies" in a D-dimensional space according to the historical experiences of its own and its colleagues. Particle has both a position, xi , and a velocity vi , which in "standard" PSO (SPSO), are updated as follows: • Each particle tries to modify its position using the following information:

- the current positions,
- the current velocities,
- the distance between the current position and pbest,
- the distance between the current position and the gbest.

The modification of the particle's position can be mathematically modeled according to the following equation

:$V_i^{k+1} = c_0 V_i^k + c_1\, rand_1(\ldots) \times (pbest_i - s_i^k) + c_2\, rand_2(\ldots) \times (gbest - s_i^k)$ (1)

where,
v_i^k: velocity of agent i at iteration k.
c_j: weighting factor rand : uniformly distributed random number between 0,and 1 s_i^k:current position of agent i at iteration k,
pbest:pbest of agent i
gbest: gbest of the group.

particle update position
$s_i^{k+1} = s_i^k + V_i^{k+1}$ (2)

3.2 Differential Evolution Algorithm

Differential Evolution Differential Evolution (DE) is also a population-based optimization algorithm. It has been applied to classical optimization and multi-objective optimization .DE creates new candidate solutions by combining existing, ones, via three evolutionary operators: mutation crossover and selection. The classical DE (crossover) operator is given as:

$V_i^j = x^t_{I1} + F(x^t_{I2} - x^t_{I3})$
$x^{t+1}_{i,j} = v^t_{i,j}$ rand() < pcr
$x^t_{i,j}$ otherwise

3.3 Hybrid PSO and DE

Hybridization has bowed out to be an effective and competent way to design high-performance optimizers, which is witnessed by the rapid evolution of diverse hybrid optimizers in the precedent decade. As a special and ambassador affiliate in the family of hybrid optimizers, DEPSO has received much consideration from researchers that are engrossed in optimization, problem solving, and algorithm design. The optimization problem, now-a-days, is represented as an intellectual search problem, where one or more agents are employed to verify the optima on a search landscape, representing the constrained surface for the optimization problem. The algorithm which gives the hybrid of PSO and DE is:

for i = 0 to the maximum bound of the number of function evaluation do
for s = 0 to the swarm size do
for d = 0 to the problem dimension do
Update velocity by PSO method
Update position by PSO method
end for d
Compute fitness of updated position If needed, update historical information for Pi and Pg end for s
Select the best swarm as an elitism swarm
If saturation factor criteria met
Perform DE updation in the Elitism swarm
Compute fitness new solution generated
from parents as a result of DE. Replace the
parent particle with the new offspring
end if
end for i

3.4 Benchmark Functions

From the regular set of Benchmark problems available in the literature, seven important functions are chosen to test the performance of Hybrid PSODE. All the benchmark problems chosen have different ranges. In our experiment the problem size for all the problems is set to 20. The tables are listed in below:

Table 1: Benchmark Functions

S.no	*Benchmark Function*	*Formulae*	*Range*
1	Sphere	$F(x)=\sum x_i^2$	Xi ∈[-5.12,5.12]
2	Griewank	$F_4 = 1+\sum_{i=1}^{p} X_i^2/4000 - \prod_{i=1}^{p} \cos(xi/\sqrt{i})$	Xi ∈[-600,600]
3	Ackley	$F(x)=20+e-20\exp(-0.2\sqrt{1/p\sum_{i=1}^{p} x_i^2}) - \exp(1/p\sum_{i=1}^{p} \cos(2\pi r))$	Xi ∈[-30,30]
4	Rosenbrock	$F(x)= \sum_{i=1}^{p-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	Xi ∈[-2.048,2.048]
5	Rastrigin	$F(x)=10p+(\sum_{i=1}^{p}(x_i^2 - 10\cos(2\pi r)))$	Xi ∈[-5.12,5.12]
6	Penalized	$f5 = \pi/D\{10\sin^2(\pi y_1)+\sum\{1+10\sin^2(\pi y_i+1\}+(y_d-1)^2\}+\sum \mu(x_i, 10, 100, 4)$ where $y_i = 1+1/4(x_i+1)$	xi ∈ [−50, 50]
7	Penalized16	$f6 = 0.1\{10\sin^2(3\pi x_1) + \sum(x_i-1)^2\{1+10\sin^2(3\pi x_i+1)\}+(x_d-1)^2\{1+\sin^2(2\pi xD)\}\}+\sum \mu(xi, 5, 100, 4)$	Xi ∈[-50,50]

4. Parameters Setup

In this paper the para meter setting are as swarm size = 30. The inertia weight w is set to 0.25. c1 and c2 both are set to 2.05. Global variants of benchmark function are considered. X max and X min are the upper and lower bounds of the decision variables. Whenever the designed position of particles exceeds the X max or lowers than the X min , particle location is set to X max or X min respectively. This term paper presents an experiment on hybrid of PSODE. For best suited result, seven benchmark function is explained previously is selected. In table 2 bold values are best values.

Table 2: PSO with Mean and Standard Deviation

PSO BM fun.	fit ness	ITERATION 500	1000	1500	2000	2500
sp	mean	14.964	12.2789	20.6365	20.0015	15.9969
here	std dv	0.027078	0	5.55565	3.41615	5.11149
Grie	mean	1301.12	1279.28	1306.95	1423.87	1405.93
wank	std dv	69.5251	20.1879	22.0485	42.152	36.5914
Ack	mean	19.3142	19.2947	19.338	19.6342	19.3043
ley	std dv	0.004305	0.086233	0.012162	0	0.0428579
Rose n	mean	1.05E+09	1.15E+09	1.10E+09	1.15E+09	1.16E+09
brock	std dv	7.99E+07	4.24E+06	3.53E+07	2.85E+07	6.78E+07
Ras	mean	515.896	538.347	529.436	530.165	548.371
trigin	std dv	0	6.46464	5.9547	9.17633	17.7225
Pen alize	mean	492.697	493.531	493.028	493.241	492.893
d	std dv	1.0118	0.224248	0.352107	0.31471	0.282679
Penal iz	mean	22105.5	23350.4	23856.2	23982.2	23556.8
ed16	std dv	968.262	1707.46	1084.28	639.304	81.6777

Table 2: Hybrid PSODE with Mean and Standard Deviation

PSODE Bm fun.	fit ness	ITERATION 500	1000	1500	2000	2500
sph	mean	**17.139**	**19.7597**	**21.5081**	**21.2666**	**16.9311**
ere	std dev	1.43567	3.43925	0.0778314	0.256601	0.283526
e wan	mean	**1399.59**	**1300.78**	**1322.54**	1399.61	**1493.33**
k	std dev	81.1079	19.4243	60.4309	12.7501	24.7457
Ack	mean	**19.5408**	**19.3219**	**19.5695**	**19.5004**	**19.5854**
ley	std dev	0	0.111117	0.0280699	0.022307	0.01776
en broc	mean	**1.06E+09**	**1.21E+09**	**1.08E+09**	**1.15E+09**	**1.17E+09**
k	std dev	4.82E+07	3.46E+07	2.93E+07	4.48E+07	4.95E+07
Ras trigi	mean	**534.706**	**550.368**	**555.462**	**538.634**	**557.532**
n	std dev	6.1123	14.2541	7.40253	8.17747	16.7961
a lize	mean	492.988	492.249	**493.085**	**493.622**	**493.072**
d	std dev	0.323117	0.506643	0.184595	0.488817	0.25361
a lize	mean	**23769**	**24032.6**	**24081.8**	**24276.8**	**24267.1**
d16	std dev	845.29	1185.58	797.092	966.429	190.73

5. Experimental Result

This segment focuses on the efficiency of PSO and Hybrid PSODE tested on seven different benchmark functions with 20 dimensions, given in Table 2,3. In this results has been for different iteration starting from various randomly selected points in the multidimensional search space. The PSO and Hybrid PSODE with different benchmark function are implemented in Mat lab. Recorded simulate d results are presented in Tables II,III. for each benchmark function. For each standard deviations and the best fitness objective function evaluations (Average evaluations) of 10 runs were calculated and compared.

6. Conclusion

From the conversation, it can be seen that hybridization has many beneficial applications in the Scheduling, wireless network and computer vision fields. A number of researchers have explored and implemented dissimilar approaches for optimization. The success of a scrupulous approach depends largely on the problem domain. In other words, a method that is successful to obtain best suited solution to optimize the multi benchmark functions. For real time applications we may need fast high performance optimization techniques. From the result obtained it is concluded that Hybrid PSODE has been found to have successful performance on Sphere, Griewank, Ackley, Rosenbrock, Rastrigin, Penalized, and Penalized-16.

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Author Profile

I **Preeti Soni** received BE degree in CS from CIT Engineering College, India, in 2011 and Pursuing M. Tech degree in Computer Technology from , Rungta College of Engineering and Technology (Bhilai), India. I am doing my M.Tech project under Mrs.Minu Choudhary Associate Prof. in IT department, Rungta College of Engineering and Technology (Bhilai). Presently I am working as Lecturer in Computer Science Department in RSR Rungta Group of Colleges, Bhilai (C.G).

Mrs. Minu Choudhary is a Associate Professor in IT department, in Rungta College of Engg and Technology (Bhilai).