Particle Swarm Optimization based on Island Models

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ABSTRACT

Particle Swarm Optimization (PSO) algorithm is a metaheuristic. This method has been used for solving optimization problems. As many other metaheuristics, several modifications in this method have been carried out in order to improve the performance of the search. Island models is a structured population mechanism used in evolutionary algorithms to preserve the population diversity and thus to improve their performances. In this paper, the island model concepts are embedded into the PSO algorithm to improve its diversity as well as its convergence, where the new method is referred to as island-PSO. In this approach, the particles are distrusted into separate sub-swarm named (islands). After specific generations, a number of particles run an exchange through a migration process. This process is performed to keep the diversity into the PSO algorithm and to allow the islands to interact with each other. The experimental results using a set of benchmark functions show that the island model context is crucial to the PSO performance and the comparative study shows the efficiency of using island models.

KEYWORDS

PSO, Island Model, Migration, Diversity

1 INTRODUCTION

Particle Swarm Optimization algorithm (PSO), a Evolutionary algorithm was proposed by Kennedy and Eberhart for solving complex problems [1]. It utilizes coordinated particles to explore the search space. Particles correspond to the search points, and each particle is initialized with a random position and a random initial velocity in the search space. The position and the velocity of each particle are updated along with the search process in an intelligent way, based on its own experience and on the experience of its neighbors.

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PSO has the ability to quickly converge, which can lead to a stagnation on a local optimum. In the literature, there is no way to ensure that an optimization method will give the best results for all the possible instances of a given problem.
The hybridization can be regarded as an effective means of finding a compromise between the advantages and the disadvantages of several optimization methods. In this paper, we are proposed to improve the Standard PSO algorithm by combining it with a island models.
To improve the performance of this algorithm, there are many interesting researches on hybridizations of PSO. The authors [2] has proposed a species-based PSO (SPSO). According to this method, the swarm population is divided into species of subpopulations based on their similarity. Each species is grouped around a dominating particle called the species seed. At each iteration step, the species seeds are identified and adopted as neighborhood bests for the species groups. Over successive iterations, the adaptation of the species allows the algorithm to find multiple local optima, from which the global optimum can be identified. Nakano and al. proposed a PSO approach based on the concept of tabu search. The population is divided into two swarms in this algorithm. The first swarm deals with intensification and the second one deals with diversification[3]. The authors in [4] proposed a new PSO method called AugPSO that uses two strategies: boundary-shifting and particle-position resetting. The aim of the algorithm is to optimize lattice structures. The boundary-shifting technique forces the displacement of particles towards the boundary of feasible and unrealizable regions in order to increase the convergence rate in the search space. The technique of particle-position-resetting is motivated by the mutation scheme inspired by genetic algorithms, in order to increase the diversity.

2 CONTRIBUTION

In this work we integrate the PSO algorithm with island Models. The Island-PSO starts the search by several solutions divided into sub-swarms $E_1, E_2, \dots, E_n$. The sub-swarms arrange in a T topology migration and the distributed nodes connected by arcs. Each sub-swarm is composed of a set of particles, each particle has a position in the search space denoted by $x_{id} = x_{i1}, x_{i2}, \dots, x_{id}, \dots, x_{iD}$ and it remembers the best position that it met during the process of improving the quality of its position. Each particle position defines a solution to the problem being treated. The IPSO is summarized in Algorithm 1.
In order to evaluate the proposed IPSO, 25 test functions with different characteristics have been used $(f_1 - f_{25})$. They are selected from the set of test functions of IEEE-CEC2005 [5]. We

follow the parameters and conditions of the CEC competition where the 25 repeated runs have been performed for each test function. The 25 runs have been summarized in terms of the error average (EA) of the best individual, $EA = |f(x^*) - f(x^{best})|$, noted that x^* is a given optimal solution while the x^{best} is the average best solution obtained in 25 runs.

The set of IEEE-CEC2005 test functions $(f_1 - f_{25})$ can be described as follows: the first 5 functions $(f_1 - f_5)$ are unimodal and shifted, the second 7 test functions $(f_6 - f_{12})$ are basic multimodal and shifted; the third two functions $(f_{13} - f_{14})$ are expanded multimodal; and the fourth 11 functions $(f_{15} - f_{25})$ are hybrid composition. All of them are non separable, rotated and multimodal functions containing a large number of local minima.

Initialize S_m, R_m, , μ_i, I_n
I_n: number of islands
S_m : selection strategy
R_m: replacement strategy
μ_i: iteration number of the algorithm
Select T topology
For I_n=1 to n
Initialize the parameters and I_s size of each sub-swarm;
Initialize the velocity and random position of the particles in each dimension of the search space;
Each particle $pbest_i = x_i$
Calculate f (x_i) of each particle;
Calculate gbest; // The best $pbest_i$
While (the stopping criteria is not satisfied) do
For (i ranging from 1 to I_s) do
Calculate the new velocity using equation (1);
Find the new position using the equation (2);
Calculate f (x_i) of each particle;
If (f (x_i) is better than f ($pbest_i$)) then
$pbest_i = x_i$;
If (f ($pbest_i$) is better than f (gbest)) then
gbest = $pbest_i$;
end for
If iter mod μ_i: =0)
Update (PSO= $I_1, \ldots, I_n$) / * Random Storage
For I_1.begin to I_n.end /* I_1.begin is the first element PSO et I_n.end is the final*/
Replace () / * R_m the worst particles in island ((k+1) mod I_n) Replaced by R_m best particles in the island k */
end for
End if
Iter+1= iter
Collect the best solutions for each island in the topology.
Choose the best solution.

Algorithm 1: Island Particle Swarm Optimization

The results of the IPSO for all 25 problems are reported in table 1. It is clear that, for unimodal functions (functions 1-5) using 10D, it is quite easy for the IPSO to converge to the optimal points except for function 3. In the case of multi-modality, although all functions are rotated, the algorithm is still well guided towards the optima. The only exception is problem 8, characterized with the optima on the boundary. The IPSO is probably compelled in the boundary, so it is hard to find the solution on the boundary. For the hybrid functions, we could observe that the IPSO gives better results compared to SPSO algorithm and the integration of island models can help the algorithm to explore the research space even if it cannot find the global optimal solution over the 25 runs due to the high multi-modality of those composite functions.

Since the experiments also demonstrated that IPSO is better than SPSO in most of the test functions, showing systematically that the migration topology is an important parameter of the Island Model.

Table 1: Average error rate obtained by IPSO using bidirectional ring topology

Test	Case 1	Case 2	Case 3
f_1	1.12E-14	**0.0**	**0.0**
f_2	**0.0**	**0.0**	1.11E-009
f_3	1.34E-009	1.31E-009	**1.27E-009**
f_4	1.26E-009	**0.0**	**0.0**
f_5	1.82E-005	**1.19E-009**	1.35E-009
f_6	1.36E-009	**1.42E-11**	1.56E-11
f_7	3.57E-002	**3.1E-003**	2.85E-001
f_8	2.01E+001	2.00E+001	**1.89E+001**
f_9	1.22E-001	**1.02E-001**	2.57E-001
f_{10}	**1.14E+000**	1.68E+000	1.82E+000
f_{11}	2.74E-001	2.87E-002	**2.54E-002**
f_{12}	8.79E-001	**8.21E-001**	8.90E-001
f_{13}	1.61E+000	**1.01E+000**	1.17E+000
f_{14}	3.24E+000	**2.2E+000**	2.43E+000
f_{15}	5.67E+000	4.75E+000	**4.53E+000**
f_{16}	2.68E+000	2.41E+000	**2.37E+000**
f_{17}	**3.55E+000**	3.69E+000	3.75E+000
f_{18}	5.5E-008	**4.76E-008**	4.81E-008
f_{19}	1.81E-006	**1.34E-006**	1.54E-006
f_{20}	5.19E-007	**5.26E-008**	5.57E-008
f_{21}	2.07E-006	2.00 E-007	**1.95E-007**
f_{22}	**3.47E+001**	6.89E+001	7.01E+001
f_{23}	3.23E+000	2.11E+000	**2.00E+000**
f_{24}	9.84E-001	9.76E-001	**9.45E-001**
f_{25}	2.52E+001	**1.89E+001**	1.95E+001

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