A NEW PROPOSAL FOR A MULTI-OBJECTIVE TECHNIQUE USING TRIBES AND SIMULATED ANNEALING

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Keywords: Particle Swarm Optimization, Tribes, Simulated Annealing, Multi-objective Optimization.

Abstract: This paper proposes a new hybrid multi-objective particle swarm optimizer which incorporates a particle swarm optimization approach (Tribes) and Simulated Annealing (SA). The main idea of the approach is to propose a skilled combination of Tribes with a local search technique based on Simulated Annealing technique. Besides, we are studying the impact of the place where we apply local search on the performance of the obtained algorithm which leads us to three different versions: applying SA on the archive's particles, applying SA only on the best particle among each tribe and applying SA on each particle of the swarm. In order to validate our approach, we use ten well-known test functions proposed in the specialized literature of multi-objective optimization. The obtained results show that using this kind of hybridization is justified as it is able to improve the quality of the solutions in the majority of cases.

1 INTRODUCTION

Problems with multiple objectives present in a great variety of real-life optimization problems. These problems are generally involving multiple contradictory objectives to be optimized simultaneously. Therefore, the solution is different from that of a mono-objective optimization problem. The main difference is that they have a set of solutions that are equally good. Thus multi-objective optimization has been extensively studied during the last decades. Several techniques are proposed: those which are developed in the operational research field but with great complexity and those based on meta-heuristics that find approximate solutions. Among these meta-heuristics, the Multi-Objective Evolutionary Algorithms have been considered as successful to deal with this kind of problems.

In the last years, the PSO is also adopted to solve these problems, which is the approach considered in the reported work in this paper. In fact, it consists on the adaptation of Tribes, a parameter free algorithm based on PSO to deal with multi-objective problems.

In fact, we propose in this paper, a skilled combination of Tribes with a local search technique which is SA in order to provide a more efficient behaviour and higher flexibility when dealing with the real world problems: SA is used to cover widely the solution space and to avoid the risk of trapping in non Pareto solutions and Tribes is used to accelerate the convergence. In addition, we study the impact of the place where we apply local search on the performance of the algorithm which leads us to three different versions. In our study, we use ten well-known multi-objective test functions in order to find the best one from the proposed techniques and to justify the use of the local search.

2 TRIBES

2.1 Presentation

Tribes is a PSO algorithm that works in an autonomous way. Indeed, it is enough to describe the problem to be resolved and the way of making it

Smairi N., Bouamama S., Ghedira K. and Siarry P..
A NEW PROPOSAL FOR A MULTI-OBJECTIVE TECHNIQUE USING TRIBES AND SIMULATED ANNEALING .
DOI: 10.5220/0003538301300135
In *Proceedings of the 8th International Conference on Informatics in Control, Automation and Robotics* (ICINCO-2011), pages 130-135
ISBN: 978-989-8425-74-4

at the beginning of the execution. Then, it is the role of the program to choose the strategies to be adopted (Clerc, 2006).

2.2 Tribes Components

- The particle informer: A particle A is an informer of a particle B, if B is capable of reading the best position visited by A.
- The tribe: In the general case, a given particle A can not inform the rest of the other particles of the swarm. That's why we define the tribe, which is a subset of the swarm, where every particle is capable of communicating directly with the rest of the tribe's particles.
- The swarm: it is formed by a set of tribes; each one is looking to finding a local optimum. A group of decisions is therefore necessary to find the global optimum. For this reason, tribes have to communicate between themselves.
- Quality of a particle: The notion of a good or bad particle is relative to its tribe. We organize particles, belonging to the same tribe according to their fitness evaluations. As a result, we can define the best particle and the worst particle following every tribe.
- Quality of a tribe: to decide if a tribe T is good or bad, we generate a random number t between 0 and n (n being the size of T). If the number of good particles is bigger than t, then the tribe is considered as a good one. Otherwise, the tribe is bad.

2.3 Tribe Evolution

The evolution of a tribe involves the removal or the generation of a particle. The removal of a particle consists in eliminating a particle without risking the missing of the optimal solution. For that purpose, only the good tribes are capable of eliminating their worst elements. The creation of a particle is made for bad tribes as they need new information to improve their situations. However, we note that it is neither necessary nor desirable to perform these structural adaptations at each iteration because some time must be allowed for the information to propagate among the particles. Several possible rules can be formulated to ensure this. The rule used is: if the total number of information links is *L* after one structural adaptation, then the next structural adaptation will occur after *L*/2 iterations.

2.4 Swarm Move

The only remarkable difference between the movements of the classic PSO algorithm and those of Tribes is situated at the level of the probability distribution of the next position which is modified; it is D-spherical in the case of Tribes and D-rectangular in the case of the classic PSO.

2.5 Swarm Evolution

At the beginning, we start with a single particle forming a tribe. After the first iteration, the first adaptation takes place and we generate a new particle which is going to form a new tribe, while keeping in touch with the generative tribe. In the following iteration, if the situation of both particles does not improve, then every tribe creates two new particles: we form a new tribe containing four particles. In this way, if the situation deteriorates, then the size of the swarm grows (creation of new particles). However, if we are close to an optimal solution, the process is reversed and we begin to eliminate particles, even tribes.

3 OUR APPROACH

3.1 Preliminary Study

In the multi-objective case, we have essentially to:

- Obtain a set of solution close to the true Pareto front.
- Maintain the diversity within the found set.

For that purpose, several problems are detected:

- The choice of the informer of every particle.
- The choice of the best performance of every particle.
- A remedy to the fact that Tribes can't be considered neither a local search technique nor a global search one (Bergh, 2002).

The proposed solution to those problems consists in using the Pareto dominance to respect the completeness of every objective and to add an external archive to save the found not dominated solutions. Furthermore, the hybridization between Tribes and a local search algorithm can be considered as a competitive approach to handle difficult problems of multi-objective optimization. In order to improve the capacity of exploitation of Tribes, we apply a local search technique: SA. In fact, the local search is not going to be inevitably applied in a canonical way that is on all the particles of the swarm: we also propose two other manners, the first one consists in applying the local search only among the best particle of every tribe. The second one consists in applying it among the particles of the archive. We shall have then three versions of the algorithm.

The first one consists in applying the SA only to the particles of the archive which are situated in the least crowded zones. Let us note that, in this case, the local search is not applied unless the archive is full so that some time is allowed to the information to propagate in the swarm.

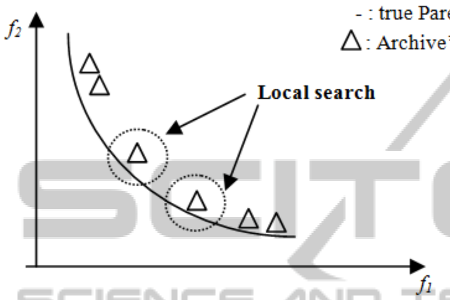

Figure 1: SA-TribesV1.

The second version of the algorithm consists in applying the SA only to the best particles of the tribes. In fact, we consider that those particles are situated in promising zones and probably they need further intensification to find out other solutions.

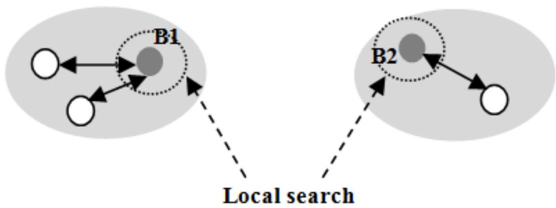

Figure 2: SA-TribesV2.

The third version consists in applying the SA to all the particles of the swarm. It is made at the moment of the swarm adaptation.

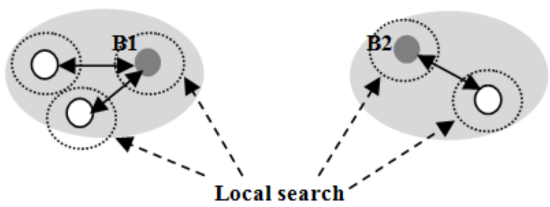

Figure 3: SA-TribesV3.

3.2 Updating the External Archive

The update of the archive consists in adding all the not dominated particles to the archive and deleting the already present dominated ones. If the number of particles in the archives exceeds a fixed number, we apply a crowd function to reduce the size of the archive and to maintain its variety. Indeed, Crowd divides the objective space into a set of hypercube.

The role of the function Crowd is to give, for every particle, the number of particles of the archive which occupy the same hypercube.

In that case, when the addition of a particle to the archive creates an overflow, we eliminate the one who has the highest Crowd.

3.3 Choosing the Particle Informer

The choice of the particle informer is similar to the case of mono-objective Tribes. Indeed, if we take a particle which is not the best of its tribe, his guide is then the best particle of the tribe. If we consider, on the other hand, the best particle of a given tribe, the informer is then some random particle from the archive.

3.4 Hybridizing Tribes with SA

Simulated Annealing (SA) is a local search method that accepts worsening moves to escape local optimal. It was proposed originally by Kirkpatrick et al. (1983), and it is based on an analogy with thermodynamics, when simulating the cooling of a set of heated atoms.

For use SA, a method for generation of an initial solution, a method for generation of neighbouring solutions and an objective function should be defined.

However, SA is essentially intended for the resolution of the combinatorial problems. Few works considered its adaptation for the continuous optimization. In our case, we are inspired from the approach of Chelouah and Siarry (2000). In that case, this method is similar to the classic SA. The difference lies essentially in the generation of the neighbourhood. It is necessary to define first of all a way to discretize the search space. In fact, the neighbourhood is defined by using the concept of "ball". A ball B(x, r) centered on x (current solution) with radius r. To obtain a homogeneous exploration of the space, we consider a set of balls centered on the current solution x with radius r_0, r_1, r_2,…r_n. Hence the space is partitioned into concentric crowns.

The n neighbours of *x* are obtained by random selection of a point inside each crown C_i, for i varying from 1 to n. Finally, we select the best neighbour *x '* even if it is worse than *x*.

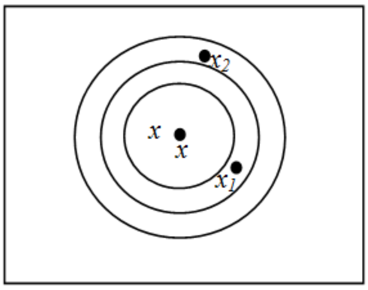

Figure 4: Generating the neighbourhood.

4 EXPERIMENTATIONS AND RESULTS

4.1 Test Functions

In order to compare the proposed techniques, we perform a study using ten well-known test functions taken from the specialized literature on evolutionary algorithms. These functions present different difficulties such as convexity, concavity, multimodality …etc. The detailed description of these functions was omitted due to space restrictions. However, all of them are unconstrained, minimization and have between 3 and 30 decision variables. Indeed, we fix the maximal size of the archive to 100 for the two-objective functions and to 150 to the three-objective ones. Moreover, we fix the maximal number of evaluations in the experimentations to 5e+4.

4.2 Metrics of Comparison

For assessing the performance of the algorithms, there are many existent unary and binary indicators measuring quality, diversity and convergence. In the literature, there are many proposed combination in order to perform a convenient study and comparison. We choose the combination of two binary indicators that was proposed in (Knowles, Thiele and Zitler, 2006): R indicator and hypervolume indicator.

4.3 Results

In order to validate our approach and to justify the use of SA, we are going to compare those proposed techniques against two other PSO-based-multi-objective approaches representative of the state of art: Mo-Tribes (Cooren, 2008) and adaptive MOPSO technique (Zielinski and Laur, 2007). Moreover, we compare them to multi-objective Tribes without local search (Tribes-V4) in order to validate the use of local search.

The binary indicators used to make the comparison measure both convergence and diversity. The results regarding the R indicator are given in table 1 (R can take values between -1 and 1 where smaller values correspond to better results). The hypervolume difference is given for all test functions in table 2. Again, smaller values mean better quality of the results because the difference to a reference set is measured.

For both indicators, we present the summary of the results obtained. In each case, we present the average of R and hypervolume measures over 25 independent runs. These values are given for the different sizes of neighbourhood.

According to these tables, we notice that the adaptive MOPSO algorithm is giving the worst results in comparison to the other techniques, presumably because this algorithm presents a classic PSO technique without sophisticated enhancements used to handle the case of multi-objective optimization. In fact, the proposed ameliorations are used to control the parameters settings.

We notice also that the hybridization with the SA gives generally better results than Tribes-V4. Moreover, SA-TribesV1 outperforms generally the others versions except for test functions S_ZDT4 and R_ZDT4 where SA-TribesV3 gives the best results. In fact, at this case, a bad convergence behaviour is detected for S_ZDT4 and R_ZDT4 for all the versions except SA-TribesV3. We note that a bad convergence behaviour is detected also with another PSO algorithm for ZDT4 in (Hu, Eberhart and Shi, 2003).

The results of Mo-Tribes are very close to those of SA-TribesV1. This can be explained by the fact that Mo-Tribes uses also a local search technique applied only on the archive's particles.

Finally, we recapitulate that SA-Tribes is very competitive as it supports both intensification and diversification. In fact, the choice of particle's informer is done in order to accelerate the swarm's convergence towards the search space zones where are situated the archive's particles. This can be considered as an intensification process. Moreover, the archive's updating is done thanks to the Crowd function that maintains the archive's diversity. This can be considered as a diversification process. Indeed, SA supports both intensification and diversification. The good neighbourhood exploration

Table 1: Results for R indicator.

Test Functions	SA-TribesV1	SA-TribesV2	SA-TribesV3	Tribes-V4	MO-Tribes	Adaptive-MOPSO
Oka2	**-1,23e-3**	-8,07e-5	-6,43e-4	8,51e-5	-1,10e-3	2,79e-2
Sympart	**1,08e-6**	4,57e-5	8,12e-5	2,39e-4	5,18e-5	7,22e-5
S_ZDT1	**3,27e-4**	1,26e-3	6,43e-4	2,79e-3	5,12e-4	1,93e-2
S_ZDT2	**6,07e-6**	1,78e-3	5,32e-5	2,80e-4	5,01e-5	9,64e-2
S_ZDT4	3,86e-3	8,16e-3	**6,74e-6**	2,07e-3	4,96e-3	4,10e-2
R_ZDT4	8,24e-3	4,59e-3	**1,16e-4**	6,98e-3	5,23e-3	8,14e-3
S_ZDT6	**1,96e-3**	5,37e-3	3,84e-3	3,05e-3	3,51e-3	1,21e-1
WFG1	3,42e-2	6,72e-2	3,11e-2	**1,22e-2**	1,53e-2	7,68e-2
WFG8	**-2,85e-2**	-1,12e-2	-4,23e-3	-4,59e-4	-2,26e-2	-1,30e-2
WFG9	**-2,14e-2**	-3,60e-3	-7,52e-3	-5,06e-3	-9,10e-3	-6,78e-3

Table 2: Results for $I_{\bar{H}}$ indicator.

Test functions	SA-TribesV1	SA-TribesV2	SA-TribesV3	Tribes-V4	MO-Tribes	Adaptive-MOPSO
Oka2	**-1,14e-3**	-9,82e-4	-1,06e-3	-1,10e-4	-1,12e-3	5,54e-2
Sympart	**1,23e-4**	1,65e-4	1,97e-4	1,28e-4	1,52e-4	2,09e-4
S_ZDT1	**6,49e-4**	4,68e-3	5,12e-3	2,05e-3	2,25e-3	6,27e-2
S_ZDT2	**3,15e-4**	3,32e-3	3,74e-4	2,87e-4	3,38e-4	2,25e-1
S_ZDT4	6,71e-3	4,03e-2	**2,51e-4**	2,16e-2	2,12e-2	1,21e-1
R_ZDT4	2,16e-2	8,74e-3	**1,07e-3**	2,06e-2	1,55e-2	2,42e-2
S_ZDT6	1,01e-2	2,64e-2	1,60e-2	6,54e-2	**7,41e-3**	3,02e-1
WFG1	1,64e-1	1,97e-1	1,44e-1	3,44e-1	**8,51e-2**	3,88e-1
WFG8	**-1,24e-1**	-7,03e-2	-7,05e-2	-2,95e-2	-1,43e-2	-8,68e-2
WFG9	-2,83e-2	-2,12e-2	-4,17e-3	-3,28e-2	**-5,72e-2**	-3,86e-2

intensifies the search towards specific zones in the search space. Besides, the SA mechanisms such as accepting worsening moves allow avoiding the risk of trapping in non Pareto solutions.

5 CONCLUSIONS

This work presented a new hybrid multi-objective evolutionary algorithm based on Tribes and SA. This hybrid aims to combine the high convergence rate of Tribes with the good neighbourhood exploration performed by the SA algorithm. Therefore, we have studied the impact of the place where we apply SA technique on the performance of the algorithm. Two widely used metrics have been used to evaluate the results. The proposed version SA-TribesV1 gave the best results almost for all the test functions except for S-ZDT4 and R-ZDT4 for which the SA-TribesV3 gave the best results.

The results showed that the hybridization is a very promising approach to multi-objective optimization. However, for some complex problems such as S-ZDT4 and R-ZDT4, SA-Tribes still need to improve its performance. As part of our ongoing work we are going to study some other strategies of displacement and adaptation in order to remedy to those problems.

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