A Study of the Efficiency of the Hybridization of a Particle Swarm Optimizer and Tabu Search

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Abstract. In this paper, we propose a hybrid Particle Swarm Optimization (PSO) called TS-Tribes which combine Tribes, a PSO algorithm free of parameters and Tabu Search (TS) technique. The main idea behind this hybridization is to combine the high convergence rate of Tribes with a local search technique based on TS. In addition, we study 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 TS on the archive's particles, applying TS only on the best particle among each tribe and applying TS on each particle of the swarm. The mechanisms proposed are validated using ten different functions from 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.

Keywords: Particle Swarm Optimization; Tribes; Tabu search; Multi-objective Optimization.

1 Introduction

In several technical fields, we are dealing with problems involving multiple contradictory objectives to be optimized simultaneously. In these problems, it is difficult to identify the best solution. 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 TS in order to provide a more efficient behavior and higher flexibility when dealing with the real world problems: TS 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.

2 Tribes

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 at the beginning of the execution. Then, it is the role of the program to choose the strategies to be adopted [2].

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. In fact, the removal or the generation of a particle is not arbitrary. 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.

3 Tabu search

The TS is introduced by Glover. It consists in the examination of a neighbourhood of a current solution x and retains the best neighbour x_0 even if x_0 is worse than x. However, this strategy can pull cycles. To prevent this kind of situation from appearing, we store the k last visited configurations in a short-term memory and we forbid to hold any other configuration which is already a part of it [1].

4 Our approach

The adaptation of Tribes to the multi-objective optimization 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. 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. Furthermore, as the PSO algorithm, Tribes can be considered neither a global optimization algorithm nor a local optimization one. Therefore, 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: TS. 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, TS-TribesV1, consists in applying the TS only to the particles of the archive. This search is applied to the particles 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.

```
Begin
  Swarm initialization
  Swarm evaluation
  Archive initialization
  While f<fmax
    For each tribe
      For each particle i
        Determination of the state of the particle
        Choice of the strategy of movement
        Choice of the informer
        Update of the position
        Evaluation
        Update of pi (best position visited by i)
        Update the best particle of the tribe
        Update the archive
      EndFor
    EndFor
    If criterion of adaptation verified
      Determination of the quality of the tribe
      Adaptation of the swarm
      Update of the adaptation criterion
    EndIf
    For each particle of the archive situated in
    the least crowded zones
      TS (stopping criterion)
    EndFor
  EndWhile
End
```

Fig. 1. TS-TribesV1 pseudo-code

The second version, TS-TribesV2, of the algorithm consists in applying the TS only to the best particle of each tribe. In fact, we consider that those particles are situated in promising zones and perhaps they need further intensification to find out other solutions. This process is repeated at each iteration of the algorithm.

The third version TS-TribesV3 consists in applying the TS to all the particles of the swarm. It is made at the moment of the swarm adaptation in order to let the propagation of the information through the swarm.

The detailed description of TS-TribesV2 and TSTribesV3 was omitted due to space restrictions.

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.

5 Experimentations and results

5.1 Presentation

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. We also fixed the size of the neighborhood to 10 for the TS algorithm. Moreover, we varied the maximal number of evaluations in the experimentations: 10e+3, 5e+4 and 10e+4.

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 [5]: R indicator and hypervolume indicator.

5.2 Results

In order to validate our approach and to justify the use of TS, we compare results with respect to multi-objective Tribes without local search (Tribes-V4) and Mo-Tribes which is a recent adaptation of Tribes to the multi-objective case introduced by Cooren [3].

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 results regarding the hypervolume indicator are omitted due to space restrictions: let us note that they have the same behavior as those of R indicator. 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 indicator measures over the 10 independent runs. These values are given for the different numbers of fitness evaluations (FES). According to that table, we notice that:

- The found fronts for test functions OKA2, WFG8 and WFG9 are better than the proposed reference fronts. Furthermore, these fronts are detected after a weak number of evaluations (10e+3).

- A bad performance behavior is noticed for S_ZDT4 and R_ZDT4 for all the versions except TS-TribesV3. We note that a bad convergence behavior is detected also with another PSO algorithm for ZDT4 in [4].
- A bad convergence behavior is detected when the FES is small (equal to 10e+4) for all the versions and for all the functions except for TS-TribesV3. This can be explained by the fact that Tribes begins with one particle and need further time to explore the search space. TS-TribesV3 has a better convergence behavior at that case thanks to the TS which is applied for all particles of the swarm.
- TS-TribesV1 outperforms generally the others versions except for test functions S_ZDT4 and R_ZDT4 where TS-TribesV3 gives the best results.
- For all the test functions, the hybridization with the TS gives generally better results than Tribes_V4.
- The results of Mo-Tribes are very close to those of TS-TribesV1. This can be explained by the fact that Mo-Tribes uses also a local search technique applied only on the archive's particles.

6 Conclusion and future work

We have introduced a new hybrid multi-objective evolutionary algorithm based on Tribes and TS. This hybrid aims to combine the high convergence rate of Tribes with the good neighborhood exploration performed by the TS algorithm. Therefore, we have studied the impact of the place where we apply TS technique on the performance of the algorithm. Two widely used metrics have been used to evaluate the results. The proposed hybridization outperformed multi-objective Tribes without TS almost in all cases. Moreover, the proposed version TS-TribesV1 gave the best results almost for all the test functions except for S-ZDT4 and R-ZDT4 for which the TS-TribesV3 gave the best results. The results showed that the hybridization is a very promising approach to multi-objective optimization. As part of our ongoing work we are going to study other hybridization between Tribes and other local search techniques.

7 References

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Table 1. Results for R indicator

Test functions	FES	TS-TribesV1	TS-TribesV2	TS-TribesV3	Tribes-V4	Mo-Tribes
OKA2	10e+3	**-1.06e-3**	-1.01e-3	**-1.06e-3**	1.21e-4	**-1.06e-3**
	5e+4	**-1.15e-3**	-1.03e-3	-1.02e-3	5.32e-5	-1.09e-3
	10e+4	-1.06e-3	-1.03e-3	-1.02e-3	1.07e-4	**-1.11e-3**
Sympart	10e+3	3.38e-2	5.35e-2	**8.29e-4**	2.16e-2	1.71e-2
	5e+4	**2.99e-5**	3.20e-5	4.68e-5	4.37e-5	3.87e-5
	10e+4	**5.47e-6**	3.77e-5	3.03e-5	4.22e-5	8.50e-6
S_ZDT1	10e+3	6.27e-1	1.81e-1	**2.65e-2**	1.02e-1	7.20e-1
	5e+4	**5.17e-4**	1.19e-3	1.21e-3	5.21e-3	7.69e-4
	10e+4	**4.10e-5**	6.65e-4	6.57e-4	3.86e-4	2.75e-4
S_ZDT2	10e+3	9.77e-2	4.01e-2	**3.04e-2**	2.64e-1	6.80e-2
	5e+4	**3.72e-5**	1.02e-3	1.23e-4	3.90e-5	4.02e-5
	10e+4	7.61e-6	8.61e-4	**3.96e-6**	1.71e-5	6.01e-5
S_ZDT4	10e+3	1.43e-1	2.28e-1	**7.94e-2**	1.39e-1	1.56e-1
	5e+4	2.82e-3	8.78e-3	**1.68e-4**	3.06e-3	8.03e-3
	10e+4	3.31e-3	6.37e-3	**1.51e-4**	1.09e-3	6.85e-3
R_ZDT4	10e+3	4.46e-1	4.98e-1	**5.31e-2**	5.11e-1	1.08e-1
	5e+4	4.24e-3	**2.35e-3**	3.38e-3	8.14e-3	7.64e-3
	10e+4	4.93e-3	2.16e-3	**2.13e-3**	5.82e-3	2.81e-3
S_ZDT6	10e+3	5.98e-1	9.33e-1	**9.41e-2**	8.75e-1	9.11e-1
	5e+4	**3.05e-3**	8.79e-3	2.42e-3	4.47e-3	4.81e-3
	10e+4	**2.65e-4**	5.06e-3	1.68e-3	1.63e-3	2.19e-3
WFG1	10e+3	5.02e-1	5.14e-1	4.97e-1	4.82e-1	**3.48e-1**
	5e+4	**2.49e-2**	4.39e-2	4.89e-2	3.23e-2	2.85e-2
	10e+4	2.21e-2	4.25e-2	4.80e-2	2.21e-2	**1.22e-2**
WFG8	10e+3	-2.76e-5	-4.51e-4	**-1.49e-2**	5.85e-5	-1.16e-3
	5e+4	**-1.69e-2**	-1.22e-2	-2.26e-3	-7.53e-4	-1.18e-2
	10e+4	-1.65e-2	-1.17e-2	-2.17e-3	-1.65e-4	**-2.34e-2**
WFG9	10e+3	-6.44e-4	-1.87e-5	-3.56e-4	-2.21e-4	**-1.90e-3**
	5e+4	**-8.21e-3**	-4.93e-3	-9.44e-3	-3.35e-3	-7.42e-3
	10e+4	**-5.73e-2**	-4.66e-3	-2.36e-2	-6.78e-3	-1.04e-2