A small population based CSA/QPSO Hybrid Evolutionary Algorithm for High-Dimensional Multimodal Optimization Problems: MCQPHE

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Abstract — This paper presents the Mini Clonal Quantum behaved PSO Hybrid Evolutionary Algorithm (MCQPHE), a hybrid evolutionary algorithm for high-dimensional and multimodal optimization problems. The proposed tool is defined as an association of the so-called Quantum behaved PSO (QPSO) with a Real Coded Clonal Selection Algorithm (RCSA), in a way that an efficient balance between local search and diversity maintenance is provided, while sustaining a good performance in terms of convergence speed and local minima issues. A class of multimodal benchmark functions is selected to illustrate the performance of our model and the results are compared with those obtained by other competitive algorithms. MCQPHE has shown to be fast and robust on handling multimodal and high-dimensional optimization problems.

I. INTRODUCTION

Optimization problems are usually characterized by a large number of variables, which can be continuous, discrete or even both. Also, there are functional and slope discontinuous regions that are non differentiable in the solution space. The use of evolutionary algorithms (EAs) has been found to be effective on handling problems of this nature and, among these techniques, the Particle Swarm Optimization (PSO) and the Clonal Selection Algorithm (CSA) were established as simple and robust tools, steadily gaining attention from the research community.

In recent years, the hybridization of evolutionary algorithms has been widely explored by the specialized literature. As different algorithms have specific advantages when solving different problems, it can be interesting to combine all (or some) specific characteristics of two algorithms, in order to achieve the better features of each technique simultaneously. There are several competitive tools developed based on this idea (see for instance [1, 2]). Moreover, promising results were reported with the use of algorithms based on artificial immune systems (AIS) synthesized with PSO [3].

In this context, a new CSA/PSO hybrid evolutionary algorithm is presented in this paper, which is defined as an association of the Quantum behaved PSO with a Real Coded Clonal Selection Algorithm. The first algorithm is an enhanced version of the original PSO, where the particles are characterized through a quantum behavior, providing a high global search capability. The latter is a variant of the CSA, which is intended to handle electromagnetic problems, assuming real coded variables and an efficient local search ability.

II. DESCRIPTION OF THE ALGORITHM

We considered several approaches in order to develop an efficient hybridization of such algorithms. In this context, a particular method has revealed robust in the preliminary tests, called Mini Clonal Quantum behaved PSO Hybrid Evolutionary Algorithm (MCQPHE). In this method, the behavior of the algorithm is improved with small populations. For the sake of clarity, a general outline of the proposed model is depicted in Fig.1.

In MCQPHE, a first swarm P_0 of size m is randomly initialized in the search space and the iterative process is started. At each iteration, we can denote two main stages: the “quantum” engine and the “clonal” engine. The first consists in updating the position of each particle just as in the classic QPSO, according to the relations given below. Further details on PSO algorithms with quantum behavior can be found in [4].

$$x_{ij} = p_{ij} + \beta \left| mbest_j - x_{ij} \right| \ln(1/u), \tag{1}$$

$$p_{ij} = c_1 x_{ij} + (1-c_2)\, pb_{gj}, \; mbest_j = \frac{1}{m}\sum_{i=1}^{m} pb_{ij}. \tag{2}$$

where *mbest* is the mainstream thought, defined as the mean of all the best positions of the population, β is called creativity coefficient and u and $r_{1,2}$ are random numbers with uniform distribution on [0,1]. The values of *pbest* and *gbest* are then updated, followed by the fitness evaluation.

The clonal engine starts with the generation of a sub-swarm S of size k, where particles are selected through the well-known roulette wheel selection, in a way that particles having best fitness values are privileged. A rank is assumed and the best $k/2$ particles are taken for cloning. Then, Nc^i clones, see (3), are generated for each particle, which are submitted to the maturation process, achieved in this work with a Gaussian mutation operator. In the following, the k best particles between the clones and the current population are selected, generating the first group of the new population.

$$N_C{}^i = round(\frac{\beta.npop}{i}). \tag{3}$$

The remaining m - k individuals of P are replaced by new ones, which are randomly generated in the search space. Furthermore, the link between the stages is completed with a fitness evaluation for the new particles, followed by an update of the *pbest* and *gbest* values. At this point, the reader could see [5] for an overview on artificial immune systems based methods, such as the RCSA [6].

```
Begin
Initialize the swarm P
Evaluate fitness
Update pbest and gbest
While g < g_max
    For each particle
        Calculate mbest and p
        Update position
        Evaluate fitness
        Update pbest and gbest
    End for
Generate S: Select k particles of P through roullete wheel selection
Set a rank h for each particle according to its fitness values and select the k/2 best ones
Generate nc(i) clones of each particle
Evaluate fitness
Select the k best solutions in S and update P
Generate round(m-k) solutions and update P
Evaluate fitness
Update pbest and gbest
End while
End
```

Fig. 1. General outline of the proposed MCQPHE.

A sensitivity analysis was performed with the aim of analyzing the influence of each parameter on the behavior of our proposed model. Despite that more details of this study will be only presented in the full version of this paper, Table I suggests a standard configuration for the parameters and some important aspects are drawn in the following.

As said before, the major goal of this hybridization is to explore the good features of each algorithm, which are: high convergence speed and global search ability of QPSO and the local search aptitude and robustness of RCSA on handling with local minimum issues. After performing some preliminary tests, we have drawn some conclusions. A small value of β must be considered in order to explore the contributions due to the clonal engine. For large values, local search problems of the quantum engine become more relevant than the effectiveness achieved with the first one. Also, the value of m must be small to properly suit the *mbest* contribution with the experience accomplished in the clonal stage. Finally, large values for the standard deviation of the Gaussian noise have shown to be harmful in terms of convergence speed. In this case, the *pbest* and *gbest* values are drastically modified during the iterations in a way that the quantum engine shows a poor behavior.

Considering the above observations, the proposed model has revealed to be a successful combination of the best features of QPSO and RCSA, as we shall see in the next section.

TABLE I
PARAMETER CONFIGURATION FOR THE MCQPHE

Parameter	m	k (%)	β_{qpso}	p_{gauss}	β_{rcsa}
Value	10	80	0.3521	0.075	10

III. EXPERIMENTAL RESULTS

With the aim of evaluating the effectiveness of MCQPHE on handling multimodal and high-dimensional problems, we have selected three complex benchmark test functions, which are frequently used in the evaluation of evolutionary algorithms. These functions are known as *Ackley*, *Rastrigin* and *Schwefel*, and referred in this work as *f1*, *f2* and *f3* respectively. In this study, we have considered a number of *30* dimensions and a maximum of *30,000* function evaluations. Notice that the stop criterion is really small when compared to the values frequently used in the specialized literature (e.g. 200,000) [7,8], in a way that the convergence velocity of MCQPHE is emphasized.

In addition, four competitive algorithms were taken to compare results with our model, namely: GA, PSO, RCSA and QPSO (see [1] for a review of GA). Results of 100 independent runs were computed for each algorithm, using an Intel Core 2 Duo E7400 @ 2.8GHz with 4GB RAM and 500 GB HD.

Fig. 2 shows the statistics obtained in the simulations for each test function, represented by the logarithm median error of the fitness value found by each algorithm. Note that our model has effectively combined the special features of each algorithm, being robust in all performed tests. Moreover, Fig. 3 shows these error values throughout the evaluations of a single run, from which an analysis about the convergence velocity of these algorithms can be developed.

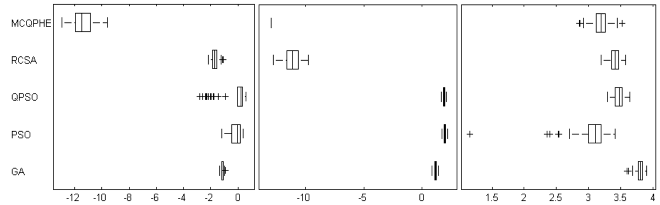

Fig. 2. Boxplots of the logarithm median error: (a) f_1, (b) f_2 and (c) f_3.

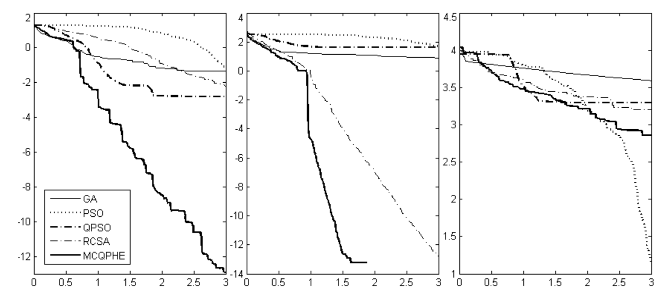

Fig. 3. Fitness values over the evaluations: (a) f_1, (b) f_2 and (c) f_3.

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