A New Collaborative Evolutionary-Swarm Optimization Technique

Rodica Ioana Lung and **D. Dumitrescu**
Babeş-Bolyai University
Department of Computer Science
Cluj Napoca, Romania
srodica,ddumitr@cs.ubbcluj.ro

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Outline of paper/presentation

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- CESO populations:
  - CRDE population;
  - SWARM population;
- Collaboration mechanism;
- Outline of CESO;
- Numerical experiments;
- Conclusions and further work.

Introduction

A new approach to solving optimization problems in dynamic environments called Collaborative Evolutionary - Swarm Optimization (CESO) is proposed.

CESO is based on the collaboration between two optimization methods: an evolutionary algorithm designed for multimodal optimization and a particle swarm optimization algorithm.

The evolutionary multimodal optimization algorithm provides a *diversity* preservation mechanism preventing the particle swarm's premature convergence to local optima.

CESO populations

CESO algorithm uses two populations of equal size:

- CRDE population: responsible for preserving diversity
- SWARM: responsible with tracking the global optimum

A collaborative mechanism between them is designed.

The CRDE population

- evolutionary multimodal optimization algorithm: Crowding based differential evolution:
- Extends the Differential evolution algorithm with a crowding scheme;
- Each offspring replaces the most similar individual among the entire population (if it is fitter);
- A *DE/rand/1/exp* scheme is used.
- Denote by $cbest$ the best individual in the CRDE population;
- Very efficient in static environments.

The SWARM

- a Particle Swarm Optimization algorithm (PSO);
- classical PSO rules:
- $x = (x_1, ..., x_n)$ - position of individual (particle) x;
- $v = (v_1, ..., v_n)$ - the velocity of particle x;
- $pbest$ represents the best position of individual x so far;
- $gbest$ represents the best individual in the whole population detected so far;
- $v_i \leftarrow v_i + c_1 * rand * (pbest_i - x_i) + c_2 * rand * (gbest_i - x_i)$,
- $x_i \leftarrow x_i + v_i$,
- $rand$ is a random number between (0,1) and c_1, c_2 are learning factors, $c_1 = c_2 = 2$;
- constant $vmin$ and $vmax$ are used to limit the velocity.

Endowed with an efficient diversity preserving mechanism PSO becomes a very powerful optimization technique.

The Collaboration mechanism

The CRDE population maintains a set of local and global optima during the entire search process.

The SWARM population is used to detect the global optimum and to indicate - if necessary - its position to the CRDE population.

Both CRDE and SWARM populations evolve in their ’natural’ manner, i.e. no additional mechanism is added to them individually.

The collaborative mechanism proposed by CESO implies a two-way communication between the SWARM and CRDE:

Transmitting information from the CRDE to the SWARM population

CRDE information is transmitted to the SWARM by copying all individuals from the CRDE to the SWARM. Thus the SWARM is actually reinitialized.

The reinitialization of the SWARM takes place if one of the followings occur:

i. a change is detected in the environment (the test is made by re-evaluating $cbest$); if this occurs all individuals are evaluated;

ii. the distance between $cbest$ and $gbest$ is lower than a prescribed threshold θ (for example 0.1)

Transmitting information from the SWARM to CRDE population

- $gbest$ replaces $cbest$ if it has a better fitness value.

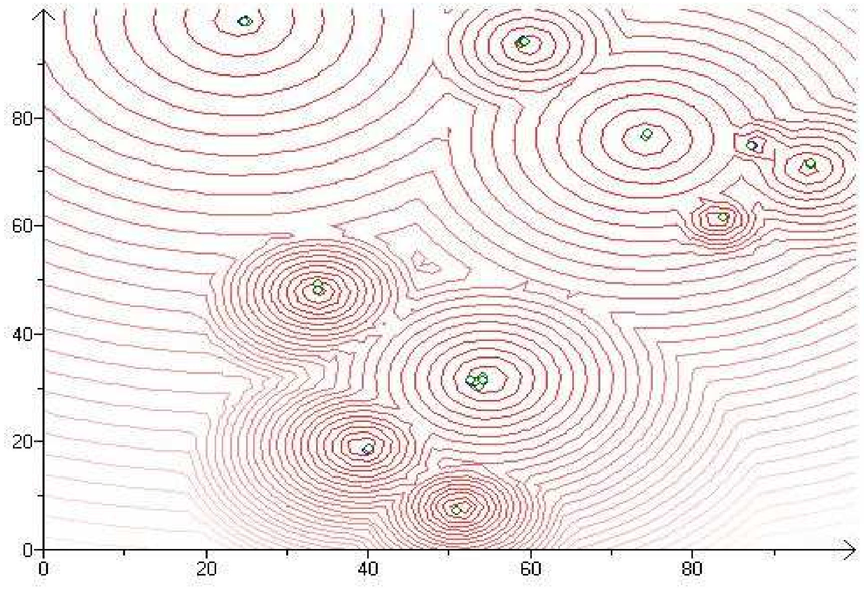

Figure 1: The CESO populations

Algorithm 1 Outline of the CESO Algorithm

```
Parameters setting;
Randomly initialize CRDE and SWARM;
Evaluate populations;
while final condition not met do
    if (change in landscape) then
        Copy CRDE to SWARM;
        Evaluate populations;
    end if
    if distance between gbest and cbest less than θ then
        Copy CRDE to SWARM;
    end if
    Update SWARM;
    Evolve CRDE;
    Evaluate populations;
    if gbest better than cbest then
        gbest replaces cbest in CRDE;
    end if
end while
```

Numerical experiments

- Moving peaks benchmark (MPB), scenario2

Table 1: Standard settings for the Moving Peaks Problem

Parameter	Setting
Number of peaks p	10
Number of dimensions d	5
Peak heights	$\in [30, 70]$
Peak widths	$\in [1, 12]$
No. of evals. between changes	5000
Change severity s	1.0
Correlation coefficient λ	0

Numerical experiments

Comparisons with:

- the Self Organizing Scouts (SOS) ;
- the Multiswarms (MPSO) methods ;
- The Particle Swarm with Speciation and Adaptation (SPSO) .

The best results obtained using the three methods considered, where applicable, are compared with those obtained by CESO.

Results are averaged over 50 runs with different random seed generator for CESO.

Parameter settings for CESO

Table 2: Parameter Settings for CESO

Parameter	Setting
CRDE and SWARM sizes	10
$vmin$,$vmax$	-0.1,0.1
$theta$	0.1

Varying shift severity

Table 3: Offline error and standard error for varying shift severity

s	CESO	mCPSO
0	**0.85± 0.02**	1.18± 0.07
1	**1.38± 0.02**	1.75± 0.06
2	**1.78± 0.02**	2.40± 0.06
3	**2.03± 0.03**	3.00± 0.06
4	**2.23± 0.05**	3.59± 0.10
5	**2.52± 0.06**	4.24± 0.10
6	**2.74± 0.10**	4.79± 0.10

The SPSO-PD reports an average of offline errors of $1.93(0.06)$ for $s = 1$.

Varying number of peaks

For MPSO the best results have been obtained for mCPSO with anticonvergence for the one peak set-up, mQSO without anticonvergence for the 10 peaks set-up and for mQSO with anticonvergence for the rest of set-ups.

Results obtained by SOS and SPSO-PD are not better than those obtained by the MPSO.

Table 4: Offline error and standard error for varying number of peaks

No. peaks	CESO	MPSO
1	**1.04**$\pm$ **0.00**	4.93$\pm$ 0.07
10	**1.38**$\pm$ **0.02**	1.75$\pm$ 0.06
20	**1.72**$\pm$ **0.02**	2.42$\pm$ 0.06
30	**1.24**$\pm$ **0.01**	2.48$\pm$ 0.06
40	**1.30**$\pm$ **0.02**	2.55$\pm$ 0.10
50	**1.45**$\pm$ **0.01**	2.50$\pm$ 0.10
100	**1.28**$\pm$ **0.02**	2.36$\pm$ 0.10

Correlation of shifts

Results are compared with average values reported by SOS.

Table 5: Offline error and standard error for varying the λ parameter

λ	CESO	SOS
0.5	**1.43**$\pm$ **0.02**	4.14
0.9	**1.46**$\pm$ **0.03**	4.09
1	**1.52**$\pm$ **0.02**	4.17

Higher dimensionality

For dimension ten, mQSO variant of MPSO reports results in the range between 4.17 and 4.70 for different parameter settings of the algorithm. A modified version of SOS reports an average offline error of 16.2 for a 20-dimensions search space and 20 peaks.

Table 6: Offline error and standard error for varying dimension of the search space

no. dimensions	CESO
10	2.51 ± 0.04
50	6.81 ± 0.07
100	24.60 ± 0.25

Effect of the collaboration

Table 7: Offline error and standard error for CESO and for the Crowding DE and PSO without any collaboration

Method	Value
CESO	**1.38$\pm$ 0.02**
Crowding DE	3.98$\pm$ 0.14
PSO	24.23$\pm$ 1.30

Conclusions and further work

- New optimization method for dynamic environments called CESO is proposed;

- Combine:
  - An evolutionary algorithm for multimodal optimization and
  - Particle swarm optimization;

- Use a simple collaboration scheme in order to transmit the diversity from the EA to PSO;

- Numerical experiments indicate CESO to be efficient for the selected benchmark;

Thank you for your attention!