Synchronous Migration in an Island Model of Differential Evolution

Petr Bujok

University of Ostrava
Department of Computer Science
30. dubna 22, 70103 Ostrava
Czech Republic
petr.bujok@osu.cz

International Student Conference on Applied Mathematics and Informatics 2012

Outline

UNIVERSITAS OSTRAVIENSIS

Global optimization process

Definition

- restricted area of solutions:
  $\Omega = [a_1, b_1] \times [a_2, b_2] \times \ldots \times [a_D, b_D],\ a_j < b_j,\ j = 1, 2, \ldots, D$
- objective function:
  $f: \quad \Omega \to \mathbb{R},\ \ D \subseteq \mathbb{R}^D$
- the global minimum is point $\boldsymbol{x}^*$ satisfying condition:
  $\forall \boldsymbol{x} \in \Omega: \quad f(\boldsymbol{x}^*) \leq f(\boldsymbol{x})$

UNIVERSITAS OSTRAVIENSIS

Differential evolution

Description

- population-based stochastic algorithm heuristically explores the area of possible solutions Ω
- possible solutions are represented as vectors: $\boldsymbol{x_i} = \{x_{i,1},\ x_{i,2},\ \ldots x_{i,D}\}$ and create population of individuals $P = \{\boldsymbol{x_1},\ \boldsymbol{x_2},\ \ldots \boldsymbol{x_N}\}$
- population of possible solutions is developed in Ω by evolutionary operators in order to find solution of task $\boldsymbol{x}^*$
- from old population of *parents* a new population of *offsprings* is created and into new generation of population is selected better from couple $\{parent, offspring\}$
- evolutionary operators: *mutation*, *crossover*, *selection* and *migration*

Adaptive differential evolution

Parameters of DE algorithm

- type of mutation and variant of crossover $\longrightarrow$ *strategy*
  - eg. $DE/rand/1/bin$
- control parameter of mutation $F \in (0, 2\rangle$
  - determines length of shift of parent in mutation $\longrightarrow$ *mutant vector*
- control parameter of crossover $CR \in \langle 0, 1\rangle$
  - determines probability of selection elements from parent or mutant vector $\longrightarrow$ *offspring*
- population size *N*
  - bigger population $\longrightarrow$ more detailed exploring of solution area
  - smaller population $\longrightarrow$ faster searching process

adaptive DE is able to adapt values of the control parameters during search process leading to increase efficiency of optimization

Parallelism in evolutionary algorithms

Motivation for using parallelism in optimization

- solving of hard tasks requires large time demands
- distribution time demands of optimization algorithm among several parallel computational units
  - length of whole parallel algorithm is equivalent to length of the slowest unit
- parallel models distribute computations among several independent processes p, enable to migrate information, $p \in \langle 2, N \rangle$
- *master-slave*, *neighbourhood*, ***migration***, *hybrid*, *hierarchic*

UNIVERSITAS OSTRAVIENSIS

Parallel migration model

Model description, operation migration

- distribution population P onto k sub-populations of equal sizes and location on isolated islands
- independent development of sub-populations for several generations - epoch
- operation *migration* - moving selected individuals between islands in order to exchange information, after length of epoch
- parameters of migration model - *topology*, *granularity* - N_p, *migration rate*, *migration policy*, *migration frequency*

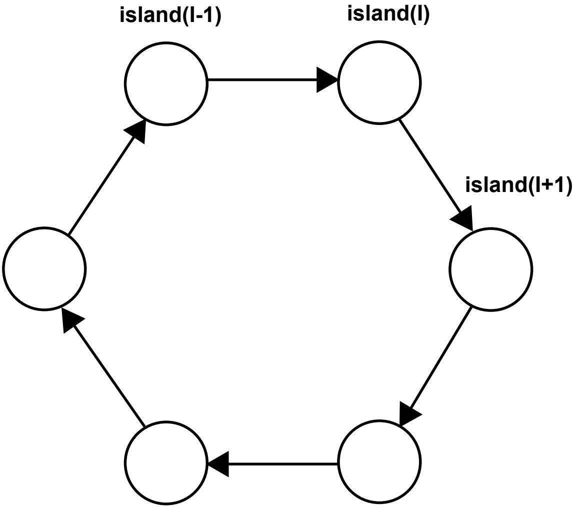
UNIVERSITAS OSTRAVIENSIS

Experiments

Experiments description

- six state-of-the-art adaptive differential evolution algorithms are paralleled by migration model with **ring** topology
- population of 60 individuals is equidistantly distributed among 6 islands with sub-populations sizes $N_p = 10$
- all islands are developed by one adaptive DE, after $nde = 5$ generations synchronous migration occurs (epoch done):
  1. 1 best and 4 randomly chosen individuals are exchanged between neighbourhood islands
  2. better island sends $1+5$ and less island $1+3$ individuals
  3. one half of individuals are exchanged between islands
- algorithm ends when satisfies condition:
  - $(f_{max} - f_{min}) \leq 1 \times 10^{-6}$ or $nfe \geq (D \times 20000)$

Experiments



Two main directions of comparison

- all algorithms run on six well known benchmark functions
- reliability rate $R \in < 0, 100 >$ - number of runs satisfying $|f_{min} - f(\boldsymbol{x}^*)| < 1 \times 10^{-4}$ in one hundred runs
- parallel percentage speed-up $p_{su} \in < 0, 100 >$:

$$p_{su} = \frac{nfe_p - nfe_s}{nfe_s} \times 100(\%),$$

  where nfe_p and nfe_s is number of function evaluation in parallel, respective sequential algorithm
- four categories of classification parallel algorithms based on R, p_{su}:
  - 1 - fast & reliable, 2 - fast & low reliable, 3 - slow & reliable, 4 - slow & low reliable

Results

Migration	Adaptive DE	Ack	Dej	Gri	Ras	Ros	Sch
$1+4$	b6e6rl	3	3	3	1	4	1
$1+4$	CoDE0	2	1	2	1	1	1
$1+4$	EPSDE	3	3	3	3	3	3
$1+4$	JADE	1	3	3	3	3	3
$1+4$	jDE	1	1	1	1	4	1
$1+4$	SaDE	4	3	4	4	4	4
$1+5, 1+3$	b6e6rl	3	3	3	1	4	1
$1+5, 1+3$	CoDE0	2	1	2	1	1	1
$1+5, 1+3$	EPSDE	3	3	3	3	3	3
$1+5, 1+3$	JADE	2	3	1	3	3	3
$1+5, 1+3$	jDE	2	1	1	1	4	1
$1+5, 1+3$	SaDE	4	3	4	4	4	3
half exch	b6e6rl	3	3	3	1	4	1
half exch	CoDE0	2	1	2	1	1	1
half exch	EPSDE	3	3	3	3	3	3
half exch	JADE	2	3	3	3	3	3
half exch	jDE	1	1	1	1	4	1
half exch	SaDE	3	3	3	4	4	3

UNIVERSITAS OSTRAVIENSIS

Results

Brief overview of fast and reliable cases

Migration	Adaptive DE	Problem	Total
$1+4$	$4/6$	$6/6$	$12\times$
$1+5, 1+3$	$4/6$	$5/6$	$11\times$
half exch	$3/6$	$6/6$	$11\times$

UNIVERSITAS OSTRAVIENSIS

Conclusion

Summary

- no significant difference among efficiency of 3 different migrations
- parallel migration model with ring topology increases efficiency compared to sequential algorithm variants
- no improvement of parallel model adaptive variants *SaDE* and *EPSDE*
- the major efficiency of parallel model adaptive variants *CoDE0*, *jDE* and *b6e6rl*

Future research will be focused on asynchronous migration models of adaptive DE variants.

UNIVERSITAS OSTRAVIENSIS

Thank you for attention!