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A robust parallel algorithm of the particle swarm optimization method for large dimensional engineering problems

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ABSTRACT

The application of the Particle Swarm Optimization (PSO) method to large engineering problems is strongly limited by the required computational cost. This limitation comes from the large number of particles needed to optimize the many-variable function, the high computational cost of its evaluation and the lack of an adequate criteria to early detect the approach of the global optimum. The first two cost sources can be mitigated by an efficient parallel implementation of the PSO method but the last one need the development of a robust convergence criterion for the algorithm. This work develops an efficient and robust optimization method by using a new convergence criterion in an asynchronous parallel implementation of PSO. In the optimization of benchmark test functions, this method showed very good performance, with parallel efficiency between 80% and 100%, and excellent robustness, always detecting the global optimum. Finally, the method was successfully applied to an actual estimation problem with 81 parameters.

1. Introduction

The numerical optimization has been subject of intense study in several fields of engineering, such as equipment and process design, process control, and parameter estimation. Two subjects of particular interest are the development of algorithms for global optimization and the optimization of large-scale engineering problems, which are computationally expensive.

The *Genetic Algorithms*, GAs [1], and the *Particle Swarm Optimization*, PSO [2], are largely used non-deterministic algorithms for global optimization, which are based on the behavior of populations (PBM – *Population Based Methods*). In the PSO, each individual particle corresponds to a potential solution of the optimization problem, located in the *n*-dimensional space formed by the Cartesian product of the optimization variables, and moving with its own velocity. Starting from an initial population, the algorithm consists of updating the velocity and the position of each particle in the swarm.

In its original form, the velocity update is composed by two terms: the *cognition* and the *social* terms. The *cognition* term expresses the effect of the best position recorded by each particle during its own movement and the *social* term brings about the influence of the best position among all particles in the swarm to the movement of each particle. The first important variant of the PSO was proposed by Shi and Eberhart [3] that consisted in the introduction of the *inertia weight* which ponders the influence of the particle velocity on its own motion. This new parameter balances the local and global characteristics

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Nomenclature

c_1	cognition parameter
c_2	social parameter
C_c	coalescence parameter
C_b	breakage parameter
E	mean value of a function or data set
f_g	the best value of the objective function known by swarm
$f_{m,i}$	the best value of the objective function known by particle i in swarm
f_d	droplet size distribution function
F	zeroth order sectional moment of the droplet volume distribution function
F_{obj}	objective function value
G	response variables
H	net particle production rate
N	permanence number counter
N_v	update counter of the inertia weight
N_p	number of particles in the swarm
N_{proc}	number of computational processors
N_{exp}	number of experiments
Q	volumetric flow rate
r_1	random number in cognition term
r_2	random number in social term
S	parallel speedup
t_{res}	hydrodynamic residence time
T	computational time
v	particle volume
$\mathbf{v}$	particle velocity vector
V_e	accident effective volume
w	inertia weight
$\mathbf{x}$	particle position vector
$\mathbf{y}$	extended particle position vector

Greek symbols

α	explanatory variables
β	model parameters
δ	errors in explanatory variables
ε	numerical tolerance
η	parallel efficiency
κ	modified PSO parameter
ξ	errors in response variables
σ	standard deviation
ς	mean number of daughters upon breakage

Subscripts

0	initial
a	absolute
$crit$	critical
f	final
g	best position in the swarm
m	best position of a particle
max	maximum
min	minimum
r	relative

Superscripts

0	initial population of the swarm
k	iteration index
n	dimension of the space