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Multi-Particle Collision Algorithm with Hooke Jeeves applied to the damage identification in the Kabe Problem

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Abstract. The hybrid metaheuristic Rotation-Based Sampling Multi-Particle Collision Algorithm with Hooke-Jeeves (RBSMPCA-HJ) is applied for damage identification in the Kabe's problem. Multi-Particle Collision Algorithm is a metaheuristic algorithm that performs a search on the solution space. With the addition of the Rotation-Based Sampling mechanism to the exploration search, a major area of the solution space has a chance to be visited. The Hooke-Jeeves is a direct search method that exploits the best solution found by the RBSMPCA, allowing to achieve better solutions. Experimental data were generated in silico, using time-invariant damages. Experiments with noiseless and noisy data were carried out. Good estimations of damage location and severity are achieved.

Keywords. Hybrid metaheuristic, rotation-based sampling, opposition-based learning, multi-particle collision algorithm, damage identification

1 Introduction

Vibration-based damage identification is an application in the field of system identification. In structures and systems, cracks and other damages cause changes in physical properties than can be detectable in the modal parameters (notable frequencies, mode shapes, and modal damping).

The damage identification problem can be described as an inverse problem and solved using optimization techniques. The solution is usually unstable. Small random errors, such as some perturbation on the system or noise in the measurements, can cause large oscillations on the solution.

Metaheuristic algorithms are powerful methods from the Computational Intelligence field that can be applied to many real-world optimization problems.

Multi-Particle Collision Algorithm (MPCA) [1] is a metaheuristic algorithm based on the physics in the nuclear reactor. This algorithm has been successfully used in the

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solution of optimization problems such as fault diagnosis [2], automatic configuration of neural networks applied to different problems such as atmospheric temperature profile identification [3], data assimilation [4], climate prediction [5] and damage identification [6–8].

This work presents the application of the hybrid algorithm Rotation-Based Sampling Multi-Particle Collision Algorithm with Hooke-Jeeves (RBSMPCA-HJ) to a benchmark problem in the structure identification area called Kabe's Problem [9].

2 Hybrid Algorithm: RBSMPCA-HJ

2.1 Multi-Particle Collision Algorithm (MPCA)

MPCA is an optimization algorithm inspired by the physics of the collision inside of a nuclear reactor [1, 10]. There are two main phenomena occurring: the scattering, where an incident particle could be scattered by a target nucleus, and the absorption, in which the particle could be absorbed by the target nucleus.

MPCA is a population-based algorithm, with a set of particles (candidate solutions) traveling inside a nuclear reactor (search space). Each particle is perturbed, creating a new particle that could be absorbed, which means that the previous particle will be substituted by the new if the new fitness is better. If a perturbed particle is worse than the original one, the particle will be recreated in a new random point within the search space. This process, called as scattering, occurs with a probability depending on the fitness of the particle.

The particles behave cooperatively in a strategy called blackboard. The best particle in the set is over-copied for all particles each some number of function evaluations. A maximum number of function evaluations (NFE_{mpca}) is defined as the stopping criterion for the MPCA. A flowchart of MPCA is presented in Figure 1

The current version MPCA is implemented in FORTRAN 90 and uses MPI libraries for parallel processing.

2.2 Rotation-Based Learning (RBL) and Rotation-Based Sampling (RBS)

The RBL concept is an extension of the Opposition-Based Learning (OBL) and the Quasi-Opposition Based Learning (QOBL) mechanisms [11].

The OBL concept was introduced in 2005 by Tizhoosh [12], using the idea that the opposite point of a defined point has a probability of bringing a better solution than the original point in an optimization problem.

After the OBL mechanism, other mechanisms, such as Quasi-Opposition Based Learning, Quase-Reflective Based Learning, Center-Based Sampling Learning (CBS), and Rotation-Based Learning have been defined, getting better results than the OBL [11].

All those mechanisms have been applied to improve the performance of some Artificial Intelligence and Computational Intelligence methods, such as Artificial Neural Networks, Fuzzy Logic, and Metaheuristic Algorithms [13].

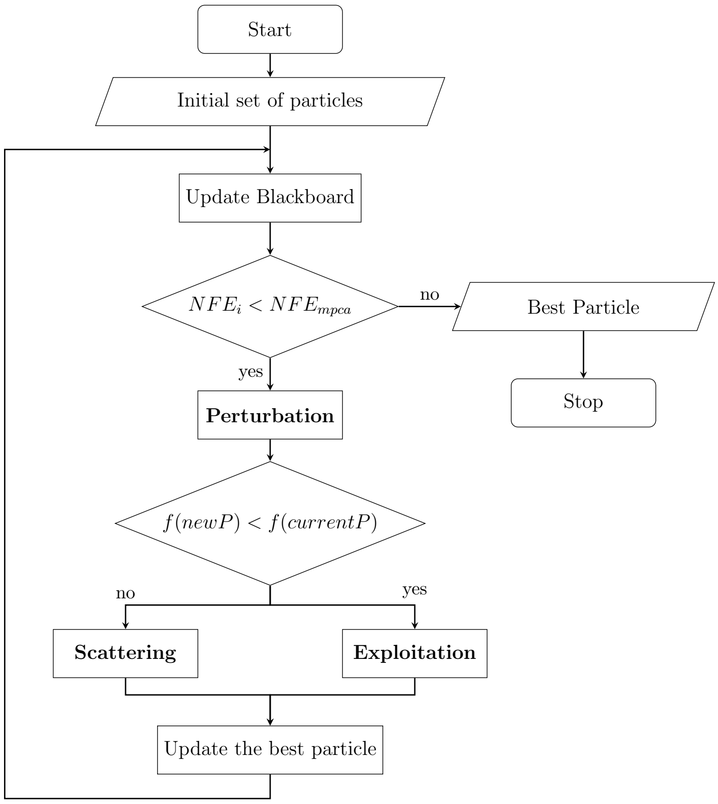

Figure 1: Multi-Particle Collision Algorithm

The Rotation-Based Sampling (RBS) mechanism is a combination of the CBS and RBL mechanisms.

2.3 Hooke-Jeeves Pattern Search Method

The pattern search method of Hooke-Jeeves (HJ) [14] is a well-known algorithm consisting of the repeated application of exploratory moves about a base point which, if successful, is followed by pattern moves. HJ method has been used in some hybrid algorithms solving the damage identification problem, such as AS+HJ [15], qG-HJ [7], and MPCA-HJ [6, 8]. Details about the algorithm of HJ can be found in the literature [14].

3 Empirical Analysis

3.1 Experimental configuration

The experiments were made in a personal computer with 4x Intel® Core™ i7-6500U CPU @ 2.50GHz, with 16 GB of memory, operating with Ubuntu 16.04.2 LTS.

The number of runs was set in 25. For the MPCA, the number of particles was set in 10, the blackboard occurs each 100,000 function evaluations, the number of function evaluations in the exploitation process is set in 1,000, while the inferior limit (IL) and superior limit (SL) in the exploitation function are set in 0.7 and 1.1, respectively. For the RBS mechanism, $\beta_0 = 3.14$ rad, and $\delta = 0.25$. In the HJ method, the parameter $\rho = 0.8$ and $h_{\min} = 1 \times 10^{-11}$.

3.2 Results of the experiments

The method is tested on a mass-spring system named Kabe's Problem. This system includes 8 masses and 14 springs in a distribution as shown in Figure 2. Dimensionless values for the mass and stiffness of the elements are shown in Table 1.

Table 1: Dimensionless mass and stiffness for the Kabe Problem

$k_{1,8}$	$k_{2,6}$	k_{3-5}	k_7	$k_{9,11,12,14}$	$k_{10,13}$
1.5	10	100	2	1000	900

m_1	m_{2-7}	m_8
0.001	1	0.002

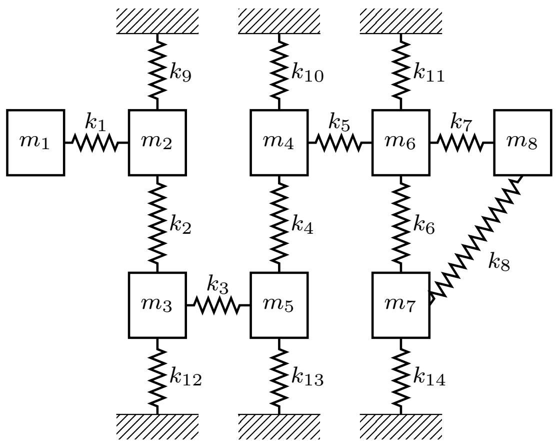

Figure 2: Kabe's Problem

Experiments were made assuming noiseless data and noisy data corrupted by a 5% noise, both generated synthetically running the direct model. Elements 4 and 7 are simulated as damaged, each one with 10% of stiffness reduction.

Figure 3 shows the mean of the damages percentage for 25 runs when noiseless data are used. Results are perfect in comparison with the original damage.

Figure 4 shows the boxplot and the Table 2 presents the mean and median for the damages for 25 runs when noisy data are used. Both damages were well estimated. For the $5th$ and the $6th$ elements appeared a dispersion in the estimations, but medians are low for both cases: 0.08 and 1.12, respectively. The mean for the $6th$ is affected by three outliers that appeared with values about of 50%.

Table 2: Mean and median of damages estimations when noisy data are used

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Mean	0.49	-0.04	-0.01	8.9	-0.15	8.4	10.1	-0.09	0.21	0.18	-0.41	0.37	0.10	-0.07
Median	-0.01	0	-0.01	10	0.08	1.1	10.0	-0.02	0.05	0.03	-0.09	0.09	0.08	-0.06

4 Final remarks

In this study, the hybrid metaheuristic RBSMPCA-HJ was applied to the damage identification in the Kabe's Problem. This method takes advantages of the exploration mechanism of the MPCA, with the complement of the Rotation-Based Sampling, and intensification power of the HJ method.

The method was tested over noiseless data and noisy data, obtaining good results in both cases.

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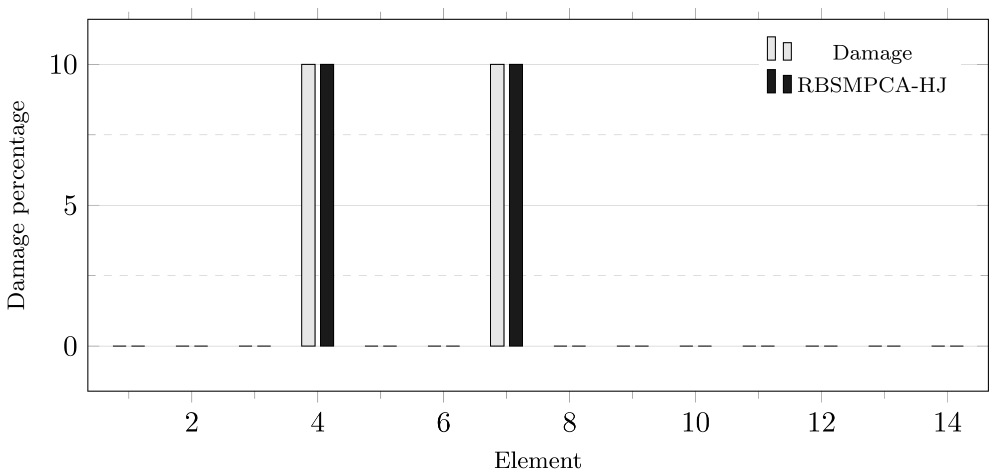

Figure 3: Results for the damage identification using RBSMPCA-HJ and noiseless data on the Kabe's Problem - Mean for 25 runs

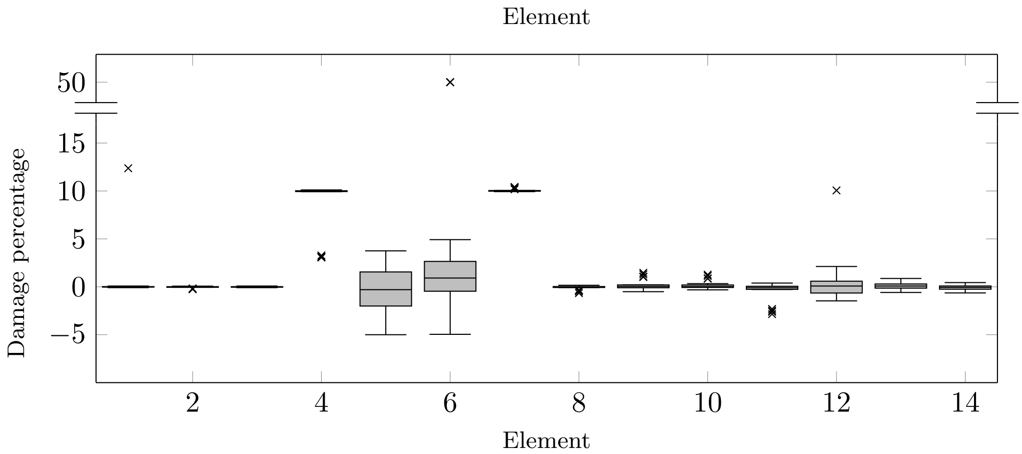

Figure 4: Results for the damage identification using RBSMPCA-HJ and noisy data on the Kabe's Problem - Boxplot for 25 runs

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