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Damage Identification of Beam Structures Using an Improved Big Bang-Big Crunch Algorithm

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***Abstract*—Beam Structures are crucial components in constructions, and damage identification of beam structures is an important research filed in engineering. Swarm intelligence algorithms have been widely used in structural damage identification for the past few years. The Big Bang-Big Crunch algorithm is one of swarm intelligence techniques with advantages of simple implementation and high efficiency. However, it is easily trapped in local optimal results and difficult of tackling with a global optimum problem, such as structural damage identification. To overcome this drawback, an improved Big Bang-Big Crunch algorithm is proposed with taking some measures. Numerical examples illustrate that damage identification of beam structures using the frequency-domain data has been realized by the improved algorithm. The improved Big Bang-Big Crunch algorithm can identify the structural damage precisely and is insensitive to measurement noises.**

Keywords—swarm intelligence; Big Bang-Big crunch; structural damage identification; beam structure; frequency domain

I. INTRODUCTION

Beam structures have found widespread use as main bearing structures in constructions, e.g. aircrafts, vehicles, bridges and buildings. Damages of the structures are often caused by external working circumstances and inner changes of material. The structural damages can reduce stiffness, mass and damping, and consequently the structures lose their loading capability. To localize and quantify structural damages of beam structures becomes important for preventing severe structural accidents.

Damage identification can be transformed into a global optimization problem in mathematic since a structure can be represented as a finite model composed of piecewise distributed mass and stiffness. To optimize an objective function established by the frequency and modal data is a common method to identify structural damages, that is, the frequency-domain method. The frequency-domain method is popular in damage identification because it is non-destructive for structures and the frequency-domain data is more convenient to obtain than other types of data [1]. However, conventional optimization techniques, e.g. least-squares estimation and Lagrangian multiplier method, are difficult of optimizing the objective function in the frequency-domain method. The reason is that conventional optimization techniques are sensitive to initial value and require the objective function being analytic. Compared with conventional techniques, swarm intelligence algorithms are more flexible and operative in global optimization problems. As they can overcome the drawbacks of conventional techniques, swarm intelligence algorithms have been widely utilized for structural damage identification in recent years. For example, Chou and Ghaboussi used the Genetic algorithm to identify the location and extent of structural damages [2]; Begambrea and Laie put forward the Hybrid Particle Swarm Optimization-Simplex algorithm for damage identification procedure based on the frequency-domain data [3]; Kang achieved structural damage identification by combining the Particle Swarm Optimization algorithm with the artificial immune system [4]; Li and Lu took advantage of the multi-swarm Fruit Fly Optimization to tackle the damage identification problem of simply supported beams and trusses [5]; Kaveh and Zolghadr identified damages of structures based on an improved Charged System Search algorithm [6].

The Big Bang-Big Crunch algorithm (BB-BC) is a kind of swarm intelligence techniques proposed by Osman and Ibrahim in 2006 [7]. It has been demonstrated that the BB-BC has the benefit of faster convergence and more convenient implementation in comparison with some other swarm intelligence algorithms [7]. The drawback of the BB-BC is that the algorithm is easily trapped into local optimum solutions in a global optimum problem. Hence, some improvements are made and an improved Big Bang-Big Crunch algorithm is present in Section II for the purpose of capitalizing on the BB-BC in damage identification of beam structures. Section III introduces the model of damage identification of beam structures using frequency-domain method. The feasibility and effectiveness of the improved algorithm in damage identification of beam structures are examined by numerical examples simulated in Section IV. Section V draws a conclusion finally.

II. THE BIG BANG-BIG CRUNCH ALGORITHM

A. The Original Big Bang-Big Crunch Algorithm

The BB-BC is one of the swarm intelligence algorithms based on the Big Bang and Big Crunch theory of the universe evolution. It consists of the following two phases:

1) The Big Bang phase: candidate solutions are blast randomly in the sreach area according to the following equation [7].

$$\mathbf{X}_i = \mathbf{X}^{\mathrm{C}} + r \cdot R(k) \cdot \mathbf{L}/2 \qquad (1)$$

$$R(k) = 1 / k \tag{2}$$

where $\mathbf{X}_i$ represents the i-th candidate solution in the n-dimensional search area, $\mathbf{X}^C$ is a temporary optimum solution called mass center, r is a normal random number, $\mathbf{L}$ is the length of the search area, N is the number of candidates, R is a function limiting the blast range and k is the iteration times.

2) The Big Crunch phase: the candidate solutions converge into a new mass center based on the following equation [7].

$$\mathbf{X}^{Cnew} = (\sum_{i=1,2\ldots,N} \mathbf{X}_i/f_i) / (\sum_{i=1,2\ldots,N} 1/f_i) \tag{3}$$

where f_i is the value of the objective function with respect to the i-th candidate solution $\mathbf{X}_i$ and $\mathbf{X}^{Cnew}$ is the new mass center. Then, replace $\mathbf{X}^C$ by $\mathbf{X}^{Cnew}$, that is,

$$\mathbf{X}^C = \mathbf{X}^{Cnew} \tag{4}$$

With repeating the Big Bang phase and Big Crunch phase in iterations, the mass center is approaching the global optimum solution.

B. The Improved Big Bang-Big Crunch Algorithm

The two phases in the original BB-BC can be operated conveniently because the formulas are not difficult for program. However, it can be found that the BB-BC converges excessively fast according to Equation (2). The value of the blast function R decreases rapidly with the iteration processing as R is an inverse proportional function with respect to the iteration time k. The over speed of the reduction of blast range (what Function R stands for) likely makes the mass center being trapped into local searching area and missing the global optimum solution. Thus, measures are taken to improve the original BB-BC as follows.

1) Modifying the blast function R: the form of the blast function R is modified as the following equation.

$$R(k) = (1 - k / k_{max})^2 \tag{5}$$

where k_{max} is the maximum number of iterations. The form of Function R is changed into a quadratic function. It can be calculated that the value of R decreased slower than that in Equation (2).

2) Producing several mass centers in later iterations: if $k \le \gamma k_{max}$, produce a new mass center $\mathbf{X}^{Cnew}$ from $\mathbf{X}^C$ in an iteration time; if $k > \gamma k_{max}$, several new mass centers $\mathbf{X}_j^{Cnew}$, $j = 1, 2,\ldots, M$ are generated from $\mathbf{X}^C$ in an iteration time with the Big Bang phase and Big Crunch phase repeating M times. γ is a constant parameter in the range of (0, 1] and M is the number of those mass centers. Revising Equation (4), the calculation of $\mathbf{X}^C$ for next iteration follows the following equation.

$$\mathbf{X}^C = (\sum_{j=1,2\ldots,M} \mathbf{X}_j^{Cnew}/f_j^{Cnew}) / (\sum_{j=1,2\ldots,M} 1/f_j^{Cnew}) \tag{6}$$

where f_i^{Cnew} is the value of the objective function with respect to $\mathbf{X}_j^{Cnew}$. Multiple mass centers provide more opportunities for $\mathbf{X}^C$ to exit a local area through the weighted average based on Equation (6). This contributes to accessing a solution closer to the global optimum solution within the limited searching area, instead of a local optimum solution.

An improved Big Bang-Big Crunch algorithm is put forward with taking the above two improvements. The improved algorithm comprises Equations (1), (3), (5) and (6), and Table I displays its process.

TABLE I. PROCESS OF THE IMPROVED ALGORITHM

- set initial population $\mathbf{X}_0^C = [x_{01}, x_{01},\ldots, x_{0n}]$;
- define the maximum number of iterations k_{max}, parameter γ, and error tolerance ε;
- for $k = 1 : k_{max}$
  - if $k \le \gamma k_{max}$, define the number of mass center $M = 1$,
  - else if $k > \gamma k_{max}$, define the number of mass center $M = m$ ($m > 1$);
  - for $j = 1 : M$
    % the Big Bang phase
    - for $i = 1 : N$ $\mathbf{X}_i = \mathbf{X}^C + r \cdot R(k) \cdot \mathbf{L}/2$, $f_i = f(\mathbf{X}_i)$ end
    % the Big Crunch phase
  - $\mathbf{X}^{Cnew} = (\sum_{i=1,2\ldots,N} \mathbf{X}_i/f_i) / (\sum_{i=1,2\ldots,N} 1/f_i)$, $f_j^{Cnew} = f(\mathbf{X}_j^{Cnew})$
  - end for
  - $\mathbf{X}^C = (\sum_{j=1,2\ldots,M} \mathbf{X}_j^{Cnew}/f_j^{Cnew}) / (\sum_{j=1,2\ldots,M} 1/f_j^{Cnew})$
  - if $|f^C - f(\mathbf{X}^C)| < \varepsilon$, break
- end for

III. MODEL FOR DAMAGE IDENTIFICATION

A cantilever beam is selected as an example for damage identification in this study. It is divided into a finite model with 10 elements, and the geometry properties are shown in Figure I. There are total 20 dofs in the cantilever beam model. Because the height-to-length ratio of the beam is 1/30 less than 1/20, the beam should be modeled as an Euler-Bernoulli beam. Hence, the shear effect is ignored, and the considering material properties of the beam are that Young's modulus E = 34 GPa and density ρ= 2800 kg/m3.

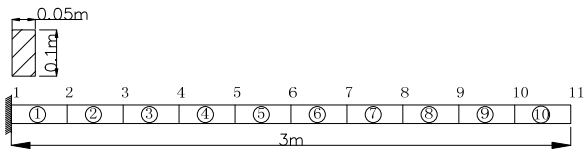

FIGURE I. THE FINITE MODEL OF CANTILEVER BEAM WITH 10 ELEMENTS.

A. Objective Function

Damage identification of beam structures using frequency-domain data is to minimize an objective function with respect to natural frequencies and mode shapes of the structure. The objective function is established as the following equation combining the calculated data with measured data [4].

$$f = \sum_{i=1,2...,NOR} \{(|\omega_i^C - \omega_i^M| / |\omega_i^M|)^2 + [1 - (\mathbf{\Phi}_i^C - \mathbf{\Phi}_i^M)^2 / (\|\mathbf{\Phi}_i^C\|^2 \|\mathbf{\Phi}_i^M\|^2)]\} \quad (7)$$

where superscript 'C' represents the calculated data and superscript 'M' stands for the measured data; *NOR* is the number of measured orders; ω_i and $\mathbf{\Phi}_i$ are the *i*-th order natural frequency and its corresponding modal respectively.

B. The Calculated Data

The natural frequency and modal of beam structures can be calculated based on a finite model. It is a generalized eigenvalue problem subject to the following equations.

$$(\mathbf{K} - \omega_i^C \mathbf{M})\mathbf{\Phi}_i^C = 0 \quad (8)$$

$$\mathbf{K} = \sum_{i=1,2...,nel} (1 - \alpha_i)\mathbf{K}_i^e \quad (9)$$

$$\mathbf{M} = \sum_{i=1,2...,nel} (1 - \beta_i)\mathbf{M}_i^e \quad (10)$$

where **K** and **M** are the assembled stiffness and mass matrixes respectively; $\mathbf{K}_i^e$ and $\mathbf{M}_i^e$ are the element stiffness and mass matrixes of the *i*-th element respectively; *nel* is the number of elements; α_i and β_i are the damage coefficient of the stiffness and mass of the *i*-th element respectively, and they stand for damage extents of elements. Note that $0 \le \alpha_i, \beta_i \le 1$, where 1 means completely destroyed and 0 represents intact.

C. The Measured Data with Measurement Noise

The measured frequency and modal data are generally influenced by environment noise in practice. Herein, artificial noise is added into the simulation of damage identification based on the following equations [8].

$$\omega_i^M = \omega_i (1 + \rho_\omega r_i) \quad (11)$$

$$\mathbf{\Phi}_i^M = \mathbf{\Phi}_i (1 + \rho_\Phi r_i) \quad (12)$$

where ρ_ω and ρ_Φ are the noise level of natural frequency and modal respectively; r_i is a normal random parameter.

IV. Numerical Examples

The original BB-BC and the improved BB-BC are applied to identify locations (the damaged element number) and extents (damage coefficient α and β) of damages in the cantilever beam shown in Figure I. Table II lists several different cases which is assumed to examine the performance of the improved BB-BC. The parameters in the improved BB-BC are: the number of candidates $N = 60$, the maximum number of mass centers $M = 2$, the maximum iteration time $k_{max} = 3000$, parameter $\gamma = 0.5$ and the measured order $NOR = 5$ (which is a half of the number of elements). Simulation of each case is carried out 50 times, and Figure II presents the statistical results where the bar represents the mean value of damage coefficient of all 50-times simulations.

TABLE II. THE LIST OF IDENTIFIED CASES

Case	*Algorithm*	*Damaged element*	*Damage extent (α, β)*	*Noise level (ρ_ω, ρ_Φ)*
1	The original BB-BC	5	(15%, 5%)	(0%, 0%)
2	The improved BB-BC	5	(15%, 5%)	(0%, 0%)
3	The improved BB-BC	5	(15%, 5%)	(0.5%, 5%)
4	The improved BB-BC	5	(15%, 5%)	(1%, 10%)
5	The original BB-BC	2, 8, 9	(5%, 0%), (15%, 5%), (30%, 10%),	(0%, 0%)
6	The improved BB-BC	2, 8, 9	(5%, 0%), (15%, 5%), (30%, 10%),	(0%, 0%)
7	The improved BB-BC	2, 8, 9	(5%, 0%), (15%, 5%), (30%, 10%),	(0.5%, 5%)
8	The improved BB-BC	2, 8, 9	(5%, 0%), (15%, 5%), (30%, 10%),	(1%, 10%)

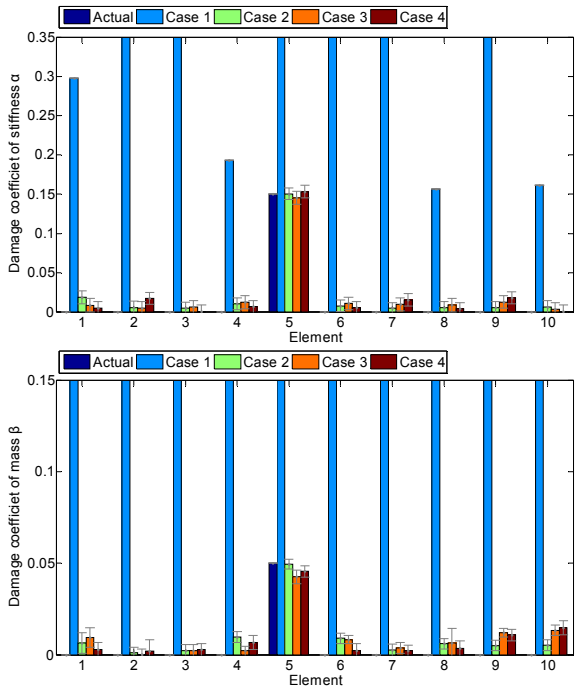

Figure II. (A)

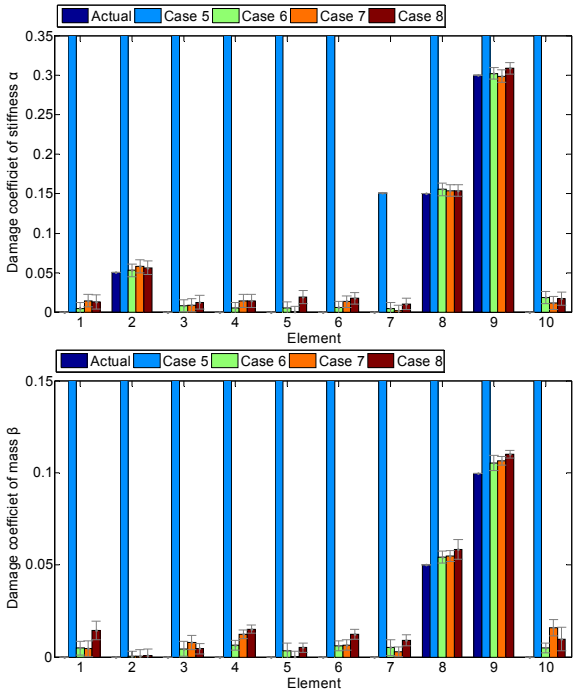

Figure II. (B)

FIGURE II. RESULTS OF SIMULATIONSL: (A) RESULTS OF CASES 1 TO 4; (B) RESULTS OF CASES 5 TO 8; .

Cases 1 to 4 are single site damage identifications where only Element 5 is destroyed, and Cases 5 to 8 are multiple sites damage identifications with Elements 2, 8 and 9 damaged. Figure II demonstrates that the original BB-BC cannot identify the locations and extents of damages; in contrast, the improved BB-BC finds out the damaged locations accurately and detects the damaged extent with tolerable errors. Compared Cases 2, 3 and 4 (or Cases 6, 7 and 8), the improved BB-BC accomplish damage identification with the impact of different noise levels. The precisions of the results are indistinguishable with the noise level up. The improved BB-BC performs insensitive to the measurement noise in structural damage identification. The maximum relative error between the actual and the simulated values is less than 2% among all the cases. This illustrates that the improved BB-BC is accurate for damage identification of beam structures. Moreover, the precision of the improved BB-BC depends on the number of candidates *N* and the maximum number of mass centers *M*. The measured order *NOR* and the maximum iteration time $k_{\max}$ determine the achievement of damage identification and the convergence speed.

V. CONCLUSIONS

In this paper, an improved Big Bang-Big Crunch algorithm is proposed for damage identification of beam structures using the frequency-domain data. It has been verified that the improved algorithm can accurately detect the locations and extents of damages in beam structures. The drawback that the original BB-BC is easily trapped into local optimum solution has been conquered by the improved BB-BC. With advantages of high precision and insensitivity to measurement noise, the improve algorithm is believed to be a useful tool in practical structural damage identification.

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