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Structural damage identification based on modified Cuckoo Search algorithm

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Abstract. The Cuckoo search (CS) algorithm is a simple and efficient global optimization algorithm and it has been applied to figure out large range of real-world optimization problem. In this paper, a new formula is introduced to the discovering probability process to improve the convergence rate and the Tournament Selection Strategy is adopted to enhance global search ability of the certain algorithm. Then an approach for structural damage identification based on modified Cuckoo search (MCS) is presented. Meanwhile, we take frequency residual error and the modal assurance criterion (MAC) as indexes of damage detection in view of the crack damage, and the MCS algorithm is utilized to identifying the structural damage. A simply supported beam and a 31-bar truss are studied as numerical example to illustrate the correctness and efficiency of the propose method. Besides, a laboratory work is also conducted to further verification. Studies show that, the proposed method can judge the damage location and degree of structures more accurately than its counterpart even under measurement noise, which demonstrates the MCS algorithm has a higher damage diagnosis precision.

Keywords: damage detection; Cuckoo search algorithm; modal assurance criteria; tournament selection strategy; discovering probability

1. Introduction

Structural damage in normal service may contain fatigue, corrosion and aging, or it may be produced by impact loads, earthquake and wind. Structural damage detection research is an active area in the field of structural health monitoring. Negligence of the local damages may cause serious engineering problems. Various approaches for damage detection have been studied and accepted by the industry and regulatory agencies. Specially, in the last few decades, researchers have proposed methods increasingly for the detection of the existence of structural damage via monitoring the change in structural responses.

Previous studies have shown that the associated changes in the structures will result in changes in the natural frequencies, mode shapes, modal strain energies, damping ratios, or other dynamic characteristics of the system. Therefore, detecting some of these properties of the damaged structure, the location and extent of the local damage could be identified. Extensive literature

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reviews on vibration-based damage detection techniques have been reported. Adams *et al*. (1979) and Narkis *et al*. (1994) identified the structure damage by using measured natural frequencies. Then by applying the curvature mode shapes, Ghafory *et al*. (2013) and Wang *et al*. (2013) localized the local damages effectively. And Yang *et al*. (2011) utilized the modal flexibility to damage detection. The natural frequency is easy to measure with a high level of accuracy, and is the most common dynamic parameter for damage detection. However, problems may arise in some structures if only natural frequency is used, since the symmetry of the structure would lead to non-uniqueness in the solution in the inverse analysis of damage detection. This problem can be overcome by incorporating the mode shape data in the analysis.

Apart from the techniques mentions above, in recent years, with the development of the mathematics and computer technique, intelligence swarm technique gained its popularity. Many real-world problems can be formulated as optimization problems with variables in continuous domains. In structural damage detection domain, the local damage of structure can be carried out using the difference between a structure's characteristics before and after a catastrophic event. One of the approaches is to formulate the certain problem as an inverse optimization problem in which the amounts of local damage are considered as the optimization variables. The target is to set these variables such that the characteristics of the model correspond to the experimentally measured characteristics of the actual damaged structure. Machavatam *et al*. (2012) applied the Neural network (NN) for damage detection. Besides, genetic algorithm (GA) as a global optimization method has been used by Buezas *et al*. (2011) for structural damage detection. Then some new optimization algorithms such as colony optimization (ACO) used by Yu *et al*. (2011) and used particle swarm optimization (PSO) applied by Guo *et al*. (2014) have been introduced in damage detection. But these swarm intelligence techniques both have common failing on slow convergence and easy to fall into local optimization.

Among the intelligence swarm algorithm, Cuckoo search algorithm by Yang *et al*. (2010) is a population-based heuristic evolutionary algorithm inspired by the interesting breading behavior such as brood parasitism of certain species of cuckoos. The CS algorithm is simple in concept, has less parameter to adjust and is easy to implement. It has been applied in many areas like constrained optimization problems and multi-objective optimization problems. Walton *et al*. (2011) modified the CS algorithm to reach high convergence to the global minimum problem even at high numbers of dimensions. Yang *et al*. (2014) utilized the CS algorithm to self-organizing systems. Wen *et al*. (2014) improved cuckoo search algorithm based on Solos and Wets local search technique and the method is proposed for constrained global optimization that relies on an augmented Lagrangian function for constraint-handling. Although the CS algorithm has been noted to be significant in many optimization problems, a few works in the field of damage identification are reported.

This paper mainly deals with the damage detection problem utilizing an improved CS algorithm. It is known that the CS algorithm also has the shortage of getting trapped the local optimal similar to other swarm intelligence algorithms. In order to solve the shortage mentions above, a new formula is introduced to the discovering probability process to improve the convergence rate and the Tournament Selection Strategy is adopted to enhance global search ability of the certain algorithm.

The performance of the improved algorithm is illustrated in two kinds of structures, i.e., a simply supported beam and a 31-bar truss. An experimental work is used for further verification of the proposed method. Results show that, local structural damages can be identified successfully even under measurement noise, which shows that the MCS algorithm is very promising for damage detection, compared to the standard CS algorithm.

2. A brief introduction to Cuckoo search algorithm

The Cuckoo search (CS) algorithm developed in 2009 by Yang and Deb (2009, 2010), is a new meta-heuristic algorithm imitating animal behavior. The optimal solutions by the CS algorithm are far better than the best solutions obtained by efficient particle swarm optimizers and genetic algorithms.

The CS algorithm is becoming very popular due to its simplicity, efficiency, and fast convergence properties and it is inspired by the cuckoo search for host nests to breed. At the most basic level, cuckoos lay their eggs in the nests of other host birds, which may be of different species. The host bird may discover that the eggs are not its own and either destroy the egg or abandon the nest all together. This has resulted in the evolution of cuckoo eggs which mimic the eggs of local host birds. During the search process, there are mainly three principle rules:

1) Each cuckoo lays one egg at a time, which represents a set of solution co-ordinates, and dumps it in a randomly chosen nest;

2) The best nests with high quality of eggs (solutions) will carry over to the next generations;

3) The number of available host nests is fixed, and a host can discover an alien egg with a probability pa $\in [0,1]$. In this case, the host bird can either throw the egg away or abandon the nest so as to build a completely new nest in a new location.

For simplicity, this last assumption can be approximated by a fraction pa of the nests being replaced by new nests (with new random solutions at new locations). For a maximization problem, the quality or fitness of a solution can simply be proportional to the objective function.

In cuckoo search, each egg can be regarded as a solution. In the initial process, each solution is generated randomly. When generating ith solution in $t+1$ generation, denoted by $x_i^{(t+1)}$, a lévy flight is performed as follows

When generating new solutions $x^{(t+1)}$ for, say cuckoo i, a lévy flight in performed

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus \text{lévy}(\lambda) \tag{1}$$

where $\alpha > 0$ is the step size which should be related to the scales of the problem. In most cases, we can use $\alpha = O(1)$. The product $\oplus$ means entry-wise multiplications. Lévy flight essentially provide a random walk while their random steps are drawn from a Lévy distribution for large steps

$$\text{Lévy} \sim \mu = t^{-\lambda},\ (1 < \lambda < 3) \tag{2}$$

Here the consecutive jumps/steps of a cuckoo essentially form a random walk process which obeys a power-law step-length distribution with a heavy tail.

In addition, a fraction pa of the worst nests can be abandoned so that new nests can be built at new locations by random walks and mixing. The mixing of the eggs/solutions can be performed by random permutation according to the similarity/difference to the host eggs.

Obviously, the generation of step size s samples is not trivial using Lévy flights. A simple scheme discussed in detail by Yang *et al*. (2010) can be summarized as

$$s = \alpha_0 (x_j^{(t)} - x_i^{(t)}) \oplus \text{Lévy}(\beta) \sim \frac{\mu}{|\nu|^{1/\beta}} (x_j^{(t)} - x_i^{(t)}) \tag{3}$$

where μ and ν are drawn from normal distributions. That is

$$\mu \sim N(0, \sigma_u^2), \quad \nu \sim N(0, \sigma_\nu^2) \tag{4}$$

with

$$\sigma_\mu = \left\{ \frac{\Gamma_{(1+\beta)\sin(\pi\beta/2)}}{\Gamma_{[(1+\beta)/2]\beta 2^{(\beta-1)/2}}} \right\}^{1/\beta} \qquad \sigma_\nu = 1 \tag{5}$$

Here Γ is the standard Gamma function.

When generating a new egg, a Lévy flight is performed starting at the position of a randomly selected egg, if the objective function value at these new coordinates is better than another randomly selected egg then that egg is moved to this new position. The scale of this random search is controlled by multiplying the generated Lévy flight by a step size. Yang *et al*. (2009) do not discuss boundary handling in their formulation, but an approach similar to PSO boundary handling is adopted here. When a Lévy flight results in an egg location outside the bounds of the objective function, the fitness and position of the original egg are not changed.

Above all, by using Lévy flight and fraction pa, CS algorithm can be proposed to various optimization problems effectively and show a high convergence rate to the trace global minimum.

The parameters pa and α introduced in the CS algorithm help the algorithm to find globally and locally improved solutions, respectively. The parameters are very important parameters in fine-tuning of solution vectors, and can be potentially used in adjusting convergence rate of algorithm. The traditional CS algorithm uses fixed value for both these parameters. These values are set in the initialization step and cannot be changed during new generations. The main drawback of this method appears in the number of iterations to find an optimal solution. If the value of pa is small and the value of α is large, the performance of the algorithm will be poor and leads to considerable increase in number of iterations. If the value of pa is large and the value of α is small, the speed of convergence is high but it may be unable to find the best solutions.

Based on these rules, the standard cuckoo search algorithm can be described as follow:

Procedure *Cuckoo search via lévy flights*

Begin
  Generation *t*=1;
    Initialized with random vector values, and initialize parameter NP, D;
    Evaluate fitness for every individual and determine the best individual with the best objective value;
    While (stopping criterion is not met)
  Get a Cuckoo randomly by lévy flights
  Evaluate fitness for the cuckoo *F*
  Choose a nest among *n* (say, *j*) randomly
    If (F_i>F_j)
        Replace *j* by the new solution;
    End if
    A fraction (pa) of worse nests are abandoned and new ones are built;
    Keep the best solution;
    Rank the solutions and find the current best.
    Update the generation number *t*=*t*+1
    End while
End.

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3. Modified the Cuckoo search algorithm

As the search relies entirely on random walks, a fast convergence cannot be guaranteed. In this paper, two modifications to the method are made with the aim of increasing the convergence rate and improving the calculation accuracy, thus making the method more practical for a wider range of applications but without losing the attractive features of the original method. We use a new search strategy based on tournament selection strategy to enhance the exploitation ability of the basic cuckoo search algorithm.

3.1 Tournament selection strategy

The Tournament Selection Strategy is adopted instead of roulette wheel to enhance the global search ability. Using the Tournament Selection Strategy, that is, first make the two comparisons of the fitness of each solution (including comparing with itself, that is, the worst solution can acquire at least one point), the bigger one will get one point, then finish comparison, each solution χ_m will acquire its total point α_m and such total points will be used to calculate the selection probability based on Eq. (6).

$$\mathrm{P_m} = \alpha_{\mathrm{m}} / \sum_{\mathrm{m}=1}^{\mathrm{SN}} \alpha_{\mathrm{m}} \tag{6}$$

where α_m denotes the total points of a solution χ_m, compared with the roulette wheel, this strategy ensures that all solutions have a finite probability of selection, so those solutions with big fitness values do not overwhelm the search strategy. Thus the probability of entrapment in a local optimum is reduced and pre matured convergence is avoided.

3.2 Dynamic discovering probability

The second modification is made to the size of the discovering probability Pa. In CS algorithm, Pa is constant and the value $pa = 0.25$ is employed. In the MCS algorithm, the value of Pa changes as the number of generations increases.

It is done for the reason that to encourage more localized searching as the individuals, or the eggs, get closer to the solution.

To improve the performance of the CS algorithm and eliminate the drawbacks lies with fixed values of Pa, the MCS algorithm uses variables Pa. In the early generations, the values of Pa must be big enough to enforce the algorithm to increase the diversity of solution vectors. However, these values should be decreased in final generations to result in a better fine-tuning of solution vectors. The values of Pa is dynamically changed with the number of generation and expressed in Eqs. (7)-(8).

where the maximum step size is $Pa_{\max}$, the minimum step size is $Pa_{\min}$, the number of total iterations is N_{iter}, the current iteration is iter, then the current step size $Pa(\mathrm{iter})$ can be as below

$$\mathrm{Pa(iter)} = \left(\frac{-4*\mathrm{Pa_{max}}}{\mathrm{iter}^2}\right) * \mathrm{N_{iter}}^2 + \left(\frac{4*\mathrm{Pa_{max}}}{\mathrm{iter}}\right) * \mathrm{N_{iter}} \tag{7}$$

$$\mathrm{Pa(iter)} = \mathrm{Pa_{min}} \ \ (\text{if } \mathrm{Pa(iter)} < \mathrm{Pa_{min}}\ ) \tag{8}$$

According to Eqs. (7)-(8), the dynamic step size is achieved. The accuracy and speed of

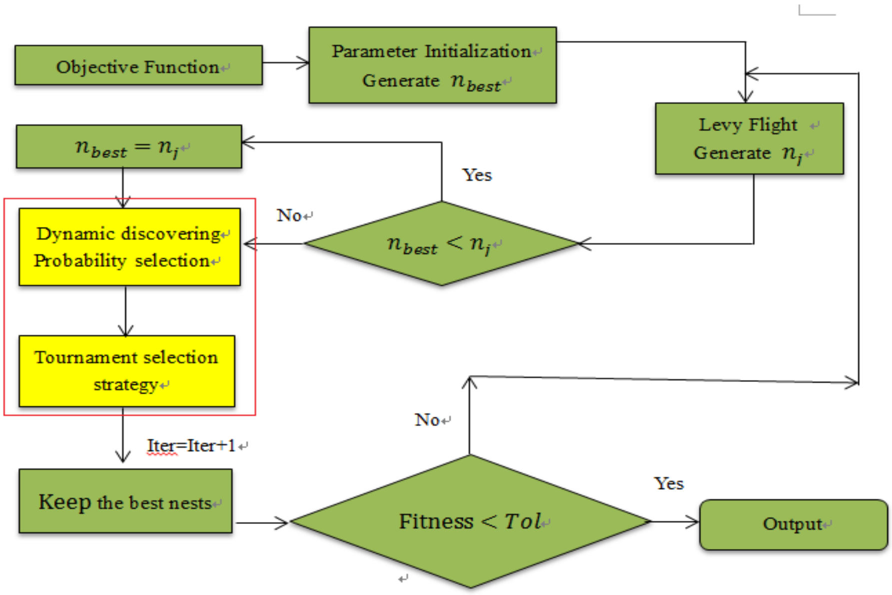

Fig. 1 Flow chats of CS algorithm and modified CS algorithm

algorithm is improved.

The basic steps of the modified Cuckoo search (MCS) algorithm can be summarized as flee shown in Fig. 1.

Through these two modifications, the Cuckoo search algorithm not only kept in the process of optimization parameters are simple to set up, the advantages of fast convergence rate, and improve the accuracy of the algorithm and avoid algorithm falls into local optimum, and can be applied to the engineering practice better.

In this paper, MCS algorithm is selected to solve the damage index objective function of the engineering structure. And then we can conclude the location and extent of the damaged structures to carry out the structural damage detection. And we choose frequency residual error and modal assurance criteria (MAC) to build up the structural objective function as below.

4. Methodology for vibration-based damage identification

In this section, the premise for techniques based on vibration responses is that damage causes a change in structural physical properties, mainly in stiffness and damping at the damaged locations. To evaluate the performance of the certain method we carried out some simulations.

4.1 Parameterization of damage

After finite element discretization, modal parameters of a structural system can be obtained from the eigenvalue equation as below

$$(\mathrm{K} - \omega_j^2 \mathrm{M})\varphi_j = 0 \tag{9}$$

where M and K are the structural mass matrix and stiffness matrix, respectively. And ω_j is the jth natural frequency and φ_j is the corresponding mode shape. In the finite element model of the damaged system, the local damage is modeled as reduction in the elemental stiffness of the system, but the other properties remain unchanged.

When a structure with nel elements is damaged, the reduction of the stiffness can be evaluated by a set of damage parameters $a_i(i = 1,2, \dots nel)$. The value range of parameter a_i is between 0 and 1.When $a_i = 1$, means that the ith element is intact while $a_i = 0$, it represents that system is completely damaged. And then the stiffness matrix of the damaged system can be written as

$$\mathrm{K_d} = \sum_{\mathrm{i=1}}^{\mathrm{nel}} \mathrm{k_i^e} \tag{10}$$

where K_d is the stiffness matrix of the damaged system, and k_i^e presents the ith elemental stiffness matrix in the global form. Damage identification implies to identify each value in the damage parameter vector$\{a\}$, based on the damage model mentioned above.

4.2 Objective function based on vibration data

It is well known that the changes of stiffness will cause the changes of the structural properties, such as natural frequencies and mode shapes. In this study, the objective function for damage detection is based on vibration data, such as natural frequencies and mode shapes. By minimizing the differences between the measured response data and the calculated one, we can locate and quantify the local damage of the certain system.

Considering the mode shape data, modal assurance criteria (MAC) proposed by Brehm *et al.* (2010) is utilized. The MAC is expressed as $\{\varphi_j{}^T\}$

$$\mathrm{MAC_j} = \frac{(\{\varphi_j\}^{\mathrm{T}} \cdot \{\varphi_j^{\mathrm{M}}\})^2}{\left(\{\varphi_j\}^{\mathrm{T}} \cdot \varphi_j\right)\left(\{\varphi_j^{\mathrm{M}}\}^{\mathrm{T}} \cdot \varphi_j^{\mathrm{M}}\right)} \tag{11}$$

where φ_j and φ_j^M are the jth calculated and measured mode shapes, respectively.

Based on MAC and taking into account the changes both in natural frequencies and mode shapes, the objective function used for damage detection is expressed as

$$\mathrm{f(x)} = \sum_{\mathrm{i=1}}^{\mathrm{s}} \left(\left(1 - \mathrm{MAC}\left(\varphi_i^h, \varphi_i^d\right)\right) + \mathrm{ER}\left(\omega_i^h, \omega_i^d\right) \right), \tag{12}$$

where s is the modal order, $\omega_i^h, \varphi_i^h, \omega_i^d, \varphi_i^d$ is the ith order frequency and mode shape of the intact and damaged system. Besides, $\mathrm{ER}\left(\omega_i^h, \omega_i^d\right) = \left|\frac{\omega_i^h - \omega_i^d}{\omega_i^h}\right| \times 100\%$, $\mathrm{MAC}\left(\varphi_i^h, \varphi_i^d\right) = \frac{\left(\{\varphi_i^h\}^T \cdot \{\varphi_i^d\}\right)^2}{\left(\{\varphi_i^h\}^T \cdot \varphi_i^h\right)\left(\{\varphi_i^d\}^T \cdot \varphi_i^d\right)}$,$i = 1,2, \dots s$. As described above, the value range of the damage parameter a_i is between 0 and 1.When $a_i = 1$, means that the ith element is intact while $a_i = 0$, it represents that system is completely damaged. Then the objective function can be

$$\mathrm{minf(x)} = \sum_{\mathrm{i=1}}^{\mathrm{s}} \left(\left(1 - \mathrm{MAC}\left(\varphi_i^h, \varphi_i^d\right)\right) + \mathrm{ER}\left(\omega_i^h, \omega_i^d\right) \right), \tag{13}$$

If the value of damage parameter vector a_i matches the given particular damage condition, the objective function will achieve its minimum value 0. In other words, when the minimum value of the objective function is identified, the corresponding parameter vector $\{a_i\}$ will indicate damage status of the structure. Then based on the value of the identify parameters a_i, we can find out the local damages of the system.

5. Numerical simulations

A simply supported beam and 31-bar truss are employed to verify the performance of CS and MCS algorithm. For the algorithm implemented, the colony size is 20, whereas other algorithm parameters are α=1, p_a=0.25 and λ=1.5. And for the parameter of the MCS are the maximum step size is $p_{a_{\max}} = 0.5$，the minimum step size is $p_{a_{\min}} = 0.05$, and α=1, and λ=1.5. The initial fitness of the objective function is 100. The total number of iteration is 2500.

To include the uncertainty in the measured data and to study the sensitivity of MCS to noise, uniformly distributed random noise is added to measured data in the simulation. To simulate measurement noise, the natural frequencies are contaminated with 1% noise and 3% noise is added to the modal displacement proposed by Kang *et al*. (2012) for all the cases. The detail of the measure noise is as below:

In this case, we investigate the effect of artificial measurement noise on the identified results. A normally distributed random error with zero mean and a unit standard deviation is added to the calculated acceleration to simulate the “noisy” measurement as shown below

$$\hat{\ddot{\mathrm{d}}} = \ddot{\mathrm{d}}_{\mathrm{cal}} + \mathrm{E_P} * \mathrm{N_{oise}} * \mathrm{var}(\ddot{\mathrm{d}}_{\mathrm{cal}}) \tag{14}$$

where $\hat{\ddot{d}}$ is the vector of polluted acceleration response; E_P is the noise level; N_{oise} is a standard normal distribution vector with zero mean and unit standard deviation; $\mathrm{var}(.)$ is the variance of the time history.

5.1 A simply supported beam

The initial geometry of the beam is shown in Fig. 2. The total number of elements and nodes are 20 and 21, respectively. In this paper, we select the steel beam as the material of the coupled system. Then the physical parameters of the certain beam are: Young’s modulus $E = 210$ GPa, mass density $\rho = 7800\ \mathrm{kg/m^3}$, the width $b = 0.1$ m, the depth $h = 0.1$ m, sectional inertia moment $I_1 = I_2 = (1/12)bh^3$, the length $L = 10$ m. And In this case it is assumed that element 4 have both 20% reduction in stiffness meanwhile element 5 has 15%, element 15 has 10%, respectively. And element 4 and element 5 are two adjacent elements as Table 1 showed. We consider both the conditions with and without noise.

Table 1 Damage scenarios of the simulation

Scenario	Model	Damage location (Element no.)	Reduction in flexural rigidity
1	Simply supported beam	4,5,15	10%,15%,20%
2	31-bar truss	4,11,18,22,30	10%,15%,15%,20%,10%

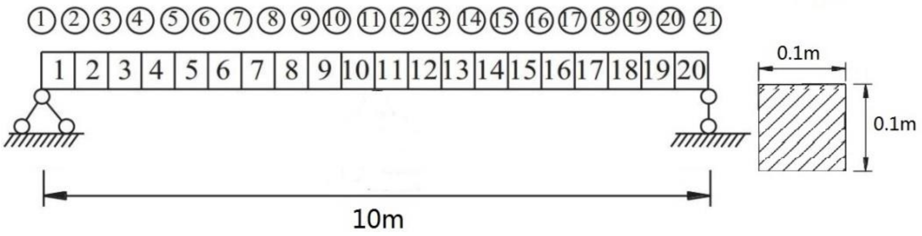

Fig. 2 The model of a simply supported beam

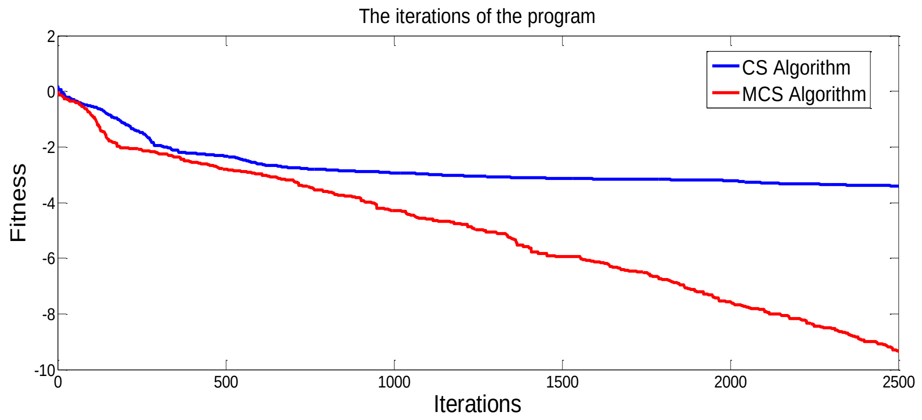

Fig. 3 The iteration process of the objective function for the simply supported beam based on CS algorithm and MCS algorithm

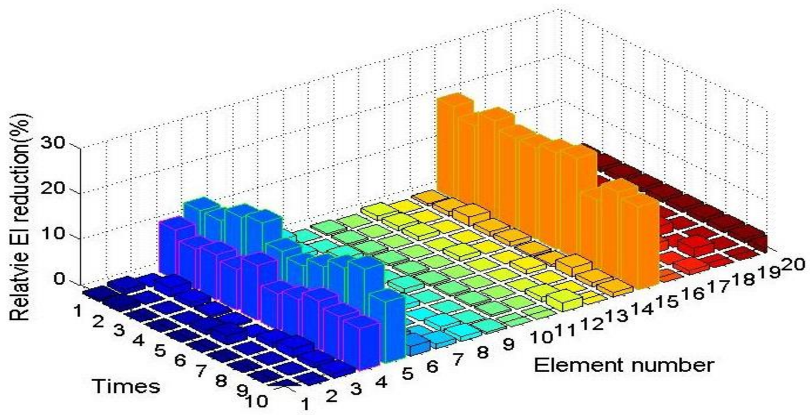

Fig. 4 The damage detection data of the simply supported beam by MCS algorithm

To show the utility of the present approach, the first three natural frequencies and mode shapes of the coupled system are calculated. The iteration process of the simply supported beam system by CS algorithm and MCS algorithm is showed in Fig. 3.

From the Fig. 3, we can see that, the convergence speed and convergence accuracy of the MCS algorithm is much higher than standard CS algorithm. Besides, all the data have been calculated 10 times for stability and accuracy as showed in Fig. 4. Above all, we can see the average results of the damge detection by CS algorithm and MCS algorithm, as showed in Fig. 5 and Table 2.

For more intuitive, we select the certain damage elements for further anlysis. The iteration of the certain damage elements by CS algorithm and MCS algorithm is showed in Fig. 6.

From the the Fig. 5, we can find the damage location and damage degrees. By comparing the detection result of the simply supported beam with artificial measurement noise to assumed damage showed in Table 2, the largest error of CS algorithm is 2.2 % in 7th element, and the largest error of MCS is 1.1% in 6th element. Then we can find out the modified CS algorithm is more effective than CS algorithm, besides, MCS algorithm is insensitive for the measurement noise and can introduce to engineering application.

5.2 A 31-bar truss

In this situation, the damage detection of a 31-bar truss system with measurement noise is

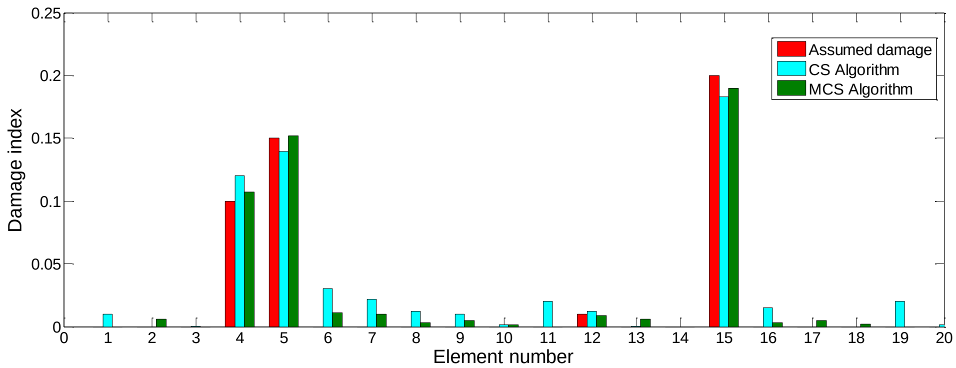

Fig. 5 Comparison of the average results for the simply supported beam under artificial measurement noise

Table 2 Identified results of the damage parameters of the simply supported beam

Element no.	Assumed damage (Relative EI reduction)	CS algorithm (Relative EI reduction)	MCS algorithm (Relative EI reduction)
3	0	0.003(0.003)	0(0)
4*	0.1	0.12(0.02)	0.107(0.007)
5*	0.15	0.1392(0.0108)	0.1516(0.0016)
6	0	0.03(0.03)	0.011(0.011)
7	0	0.022(0.022)	0.01(0.01)
9	0	0.01(0.01)	0.005(0.005)
11	0	0.02(0.02)	0(0)
13	0	0.004(0.04)	0.0062(0.0062)
14	0	0(0)	0(0)
15*	0.2	0.183(0.017)	0.19(0.01)
16	0	0.015(0.015)	0.0031(0.0031)
17	0	0.001(0.001)	0.0048(0.0048)

A* is the assumed damage element location.

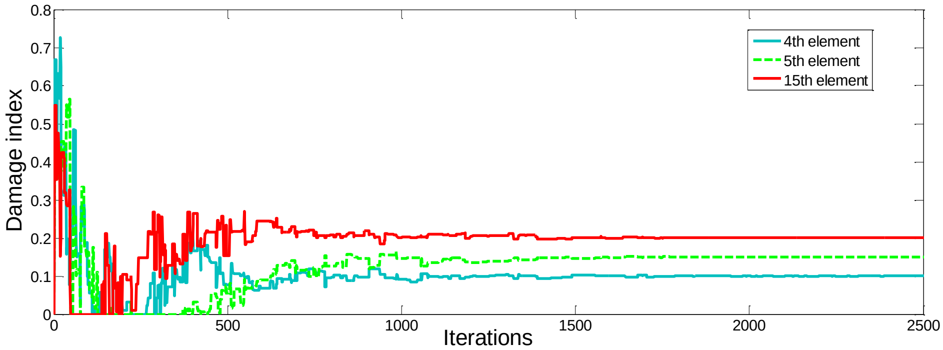

Fig. 6 The iteration processes of damage indices for the simply supported beam by MCS algorithm

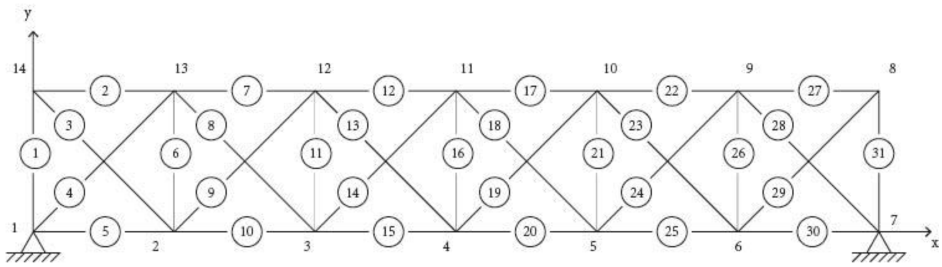

Fig. 7 The model of a 31-bar truss

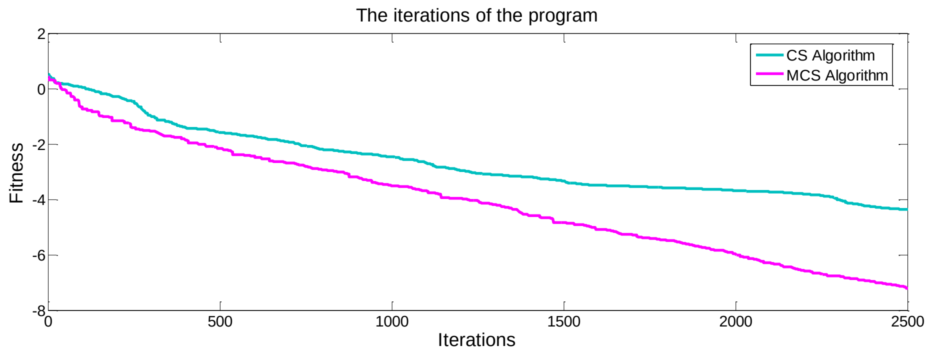

Fig. 8 The Iteration process of the objective function for the 31-bar truss based on CS algorithm and MCS algorithm

studied. The parameters are the same as above and the initial geometry of the beam is shown in Fig. 7. In this case the assumed damage location and extents is showed in Table 1. We consider both the conditions with and without noise.

The initial value for the CS algorithm and MCS algorithm and the measurement noise is the same as mentioned above. The iteration process of the 31-bar truss with the same measurement noise as situation 1 is showed in Fig. 8.

From Fig. 8, it is observed that the objective function value from MCS algorithm is closer to zero than that from the CS algorithm, indicating that the identified results from MCS algorithm are closer to the true damage extents. Moreover the damage parameters identified from MCS converge

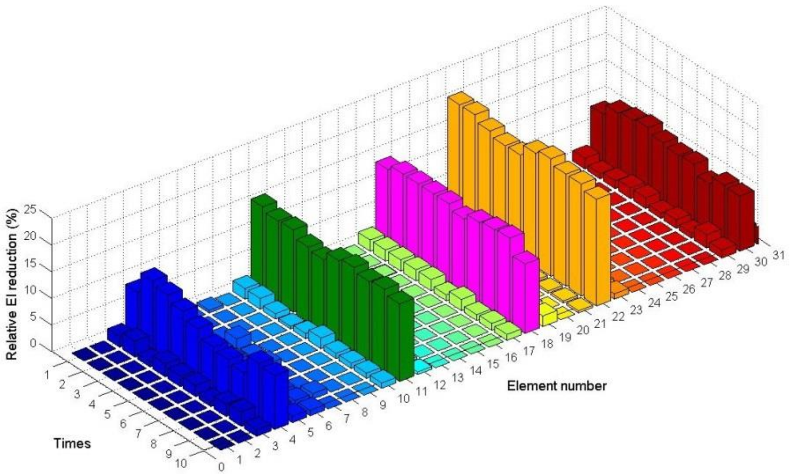

Fig. 9 The damage detection data of the 31-bar truss by MCS algorithm

Table 3 Identified results of the damage parameters of the 31-bar truss

Element no.	Assumed damage (Relative reduction(%))	CS algorithm (Relative reduction(%))	MCS algorithm (Relative reduction(%))
3	0	0.004(0.004)	0(0)
4*	10	8(2)	10.20(0.2)
5	0	1.22(1.22)	1.5(1.5)
8	0	0.003(0.003)	0(0)
9	0	1(1)	0.0032(0.0032)
10	0	2(2)	0.0026(0.0026)
11*	15	13(2)	16.2(1.2)
12	0	2(2)	1.008(1.008)
13	0	0.007(0.007)	0(0)
17	0	1.004(1.004)	1.1(1.1)
18*	15	13.03(1.97)	16(1)
19	0	3.1(3.1)	1.002(1.002)
20	0	0(0)	0(0)
21	0	2.007(2.007)	1.09(1.09)
22*	20	16.8(3.2)	19(1)
29	0	1.003(1.003)	1.006(1.006)
30*	10	12.03(2.03)	10.2(0.2)
31	0	3.002(3.002)	1.007(1.007)

A (b) is form of data (relative error).
A* is the assumed damage element location.

to the assumed values faster and more stable. all the data have been calculated 10 times for stability and accuracy is shown in Fig. 9.

Besides, we can see the average results of the damge detection by CS algorithm and MCS algorithm, as showed in Fig. 10 and Table 3. From the the Fig. 10, we can find the damage location and damage degrees by CS algorithm and MCS algorithm， respectly. What's more, we select the certain damage elements to analyse their iteration processes. The iteration of the certain damage elements by CS algorithm and MCS algorithm is showed in Fig. 11. It can be seen that even under noise, MCS algorithm still detects the damages correctly.

By comparing the detection result of the 31-bar truss with artificial measurement noise showed in Fig. 10, the largest error of CS algorithm is 3.2% in 22th element, and the largest error of MCS is 1.5% in 5th element. Then we can find out the MCS algorithm is more effective than CS algorithm, besides, MCS algorithm is insensitive for the measurement noise and can introduce to engineering application.

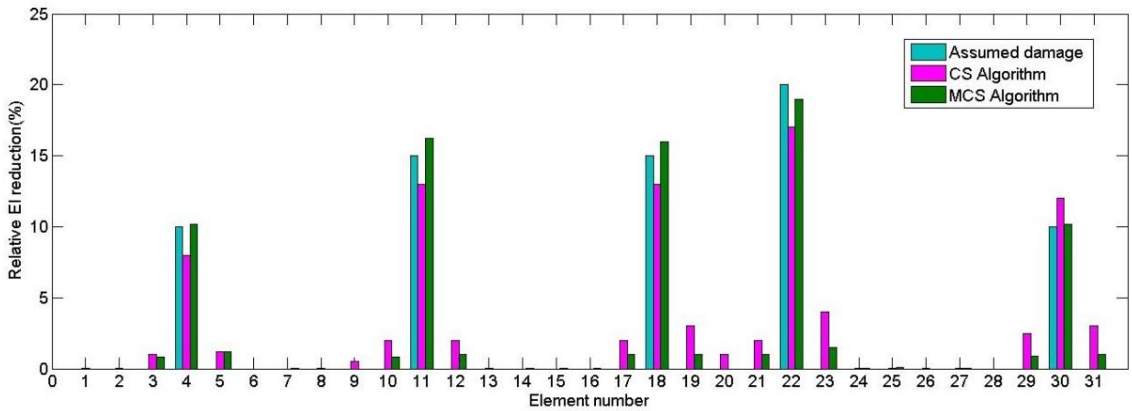

Fig. 10 Comparison of the average results for the 31-bar truss under artificial measurement noise

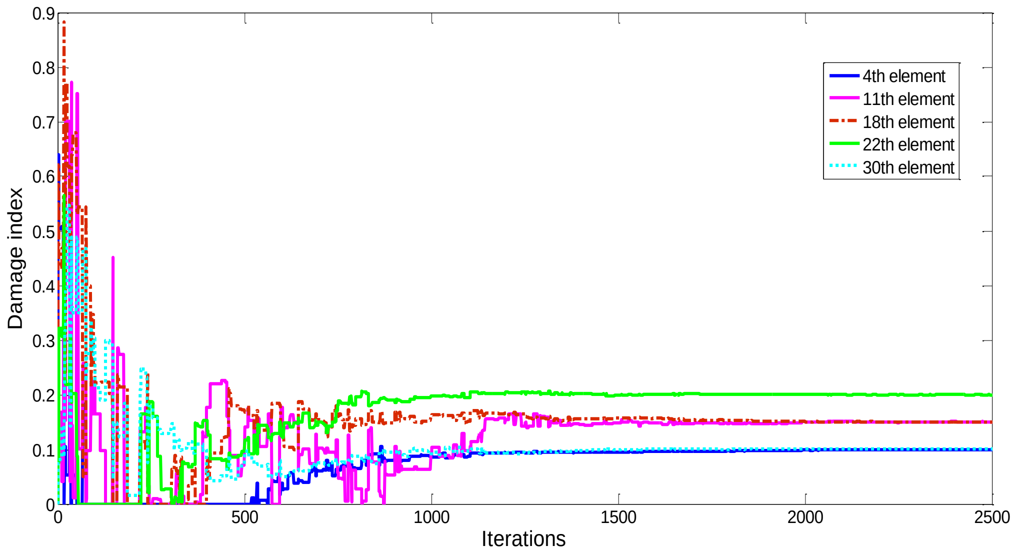

Fig. 11 The iteration process of damage indices for the 31-bar truss by MCS algorithm

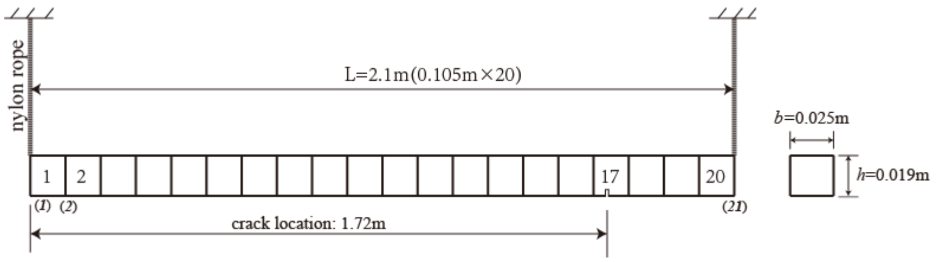

Fig. 12 Sketch of the experimental beam (dimensions are not scaled)

Table 4 The frequencies of beam from test and analytical results

Modal frequency		1st	2nd	3rd	4th	5th
Intact	Measured	22. 50	62.75	123.00	203.25	303.50
	FEM	22.85(0.35)	62.85 (0.1)	123.57(0.57)	203.55(0.3)	305. 0(1.50)
Damage	Measured	22.80	62.50	122.50	202.50	302.50

A (b) is form of data (relative error).

6. Laboratory work

The proposed method is further demonstrated with laboratory results from a free-free steel beam as shown in Fig. 12. The beam is hung by two nylon ropes at two ends. The parameters of the beam are: length $l = 2.1\ \mathrm{m}$, width $b = 0.025\ \mathrm{m}$ and height $h_0 = 0.019\ \mathrm{m}$, the Young's modulus and mass density of the material are $E = 207\ \mathrm{GPa}$ and $\rho = 7832\ \mathrm{kg/m^3}$, respectively. The damage is simulated by a crack located at 1.72m from the left free end, created by a machine saw with 1.3 mm thick cutting blade. The crack depth d_c is 3 mm. An impulsive force was applied with an impact hammer model B&K 8202 at 1.2 m from the left end. The sampling frequency is 2000 Hz. Four-second acceleration response data collected by an accelerometer model B&K 4370 at the mid-span of the beam are used to extract the first five natural frequencies of the intact and damaged beam for damage identification. The first 5 natural frequencies of the intact and the damaged beam with crack are shown in Table 4.

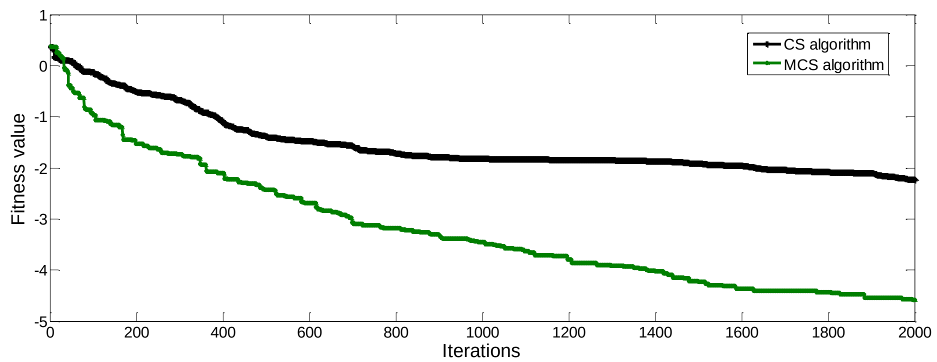

Fig. 13 The iteration process of the objective function for the experimental beam based on CS algorithm and MCS algorithm

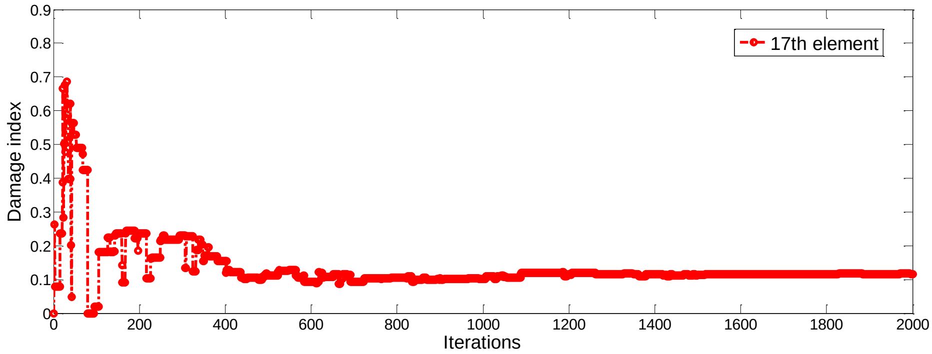

Fig. 14 The iteration process of damage indices for the experimental beam

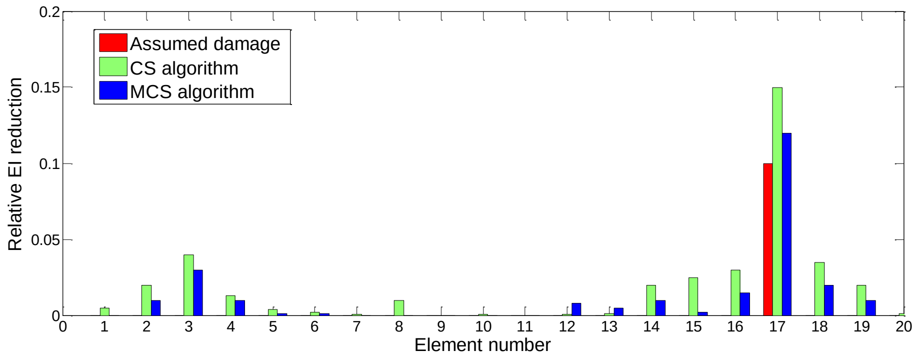

Fig. 15 Damage identification result of the experimental beam

Table 5 Identified results of the damage parameters of the experimental beam

Element no.	Assumed damage (Relative EI reduction)	CS algorithm (Relative EI reduction)	MCS algorithm (Relative EI reduction)
3	0	0.04(0.04)	0.03(0.03)
4	0	0.013(0.013)	0.0097(0.0097)
5	0	0.004(0.004)	0.001(0.001)
6	0	0.002(0.002)	0.001(0.001)
7	0	0.0008(0.008)	0(0)
9	0	0(0)	0(0)
11	0	0(0)	0(0)
13	0	0.001(0.001)	0.005(0.005)
15	0	0.025(0.025)	0.002(0.002)
16	0	0.03(0.03)	0.015(0.015)
17*	0.1	0.154(0.054)	0.125(0.025)
18	0	0.035(0.035)	0.02(0.02)
19	0	0.02(0.02)	0.01(0.01)
20	0	0.0012(0.0012)	0.001(0.001)

A (b) is form of data (relative error).
A* is the assumed damage element location.

The beam is discretized into twenty Euler beam elements with two degrees-of-freedom at each node. The crack locates at the 17th element in the finite element model. The natural frequencies calculated from the finite element model are quite close to the measured values, indicates that the initial finite element model is accurate enough for the subsequent damage identification.

As only the measured natural frequency data is used in the damage identification, the second term in the objective function of Eq. (12) is used and second term is removed. Fig. 13 and Fig. 14 indicates the iteration process of the objective function based on MCS algorithm and the iteration process of damage indices for the experimental beam.

Fig. 15 and Table 5 show the identified result by CS and MCS algorithm. One can find that the location of the damage has been identified successfully, and the identified extent of damaged element 17 is 12.5% by utilizing MCS algorithm. The true damage value is obtained by a direct identification using the measured and calculated natural frequencies with the known location of damaged element, i.e., the 17th element, and other elements are intact. It is found there are 2 large false identifications in 3th element, 4th element and 18th element. The false alarm in 3th element and 4th element may due to the reason that it is the symmetric one of 17th element. The false alarm in 18th element can be explained since 18th element is in immediate adjacent to the damage and the vibration energy in the element would be much more disturbed than those in other elements as discussed by Shi *et al*. (2000). Overall, the MCS algorithm can detect the local damage of the certain experimental beam accurately, compared to the standard CS algorithm.

7. Conclusions

A damage detection approach based on MCS Algorithm using frequency and modal data is proposed. The numerical simulations and a laboratory work illustrate that the present approach is correct and efficient for detecting structural local damages. The proposed method only needs the first few natural frequencies and mode shapes of the structure in the identification and is not sensitive to measurement noise. Simulation and laboratory results demonstrate, compared with the standard CS algorithm, the MCS algorithm is very promising for damage detection.

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