Two-Stage Damage Detection of Beam Structure Based on Improved PSO Algorithm

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Abstract. In order to solve the problem of damage location and degree identification of beam structure under multiple damage and small damage condition, a two-stage recognition method based on the improved particle swarm optimization (PSO) algorithm was proposed. Firstly, the first stage damage localization is carried out. The D-S evidence theory fusion algorithm is used to fuse element damage variable and element stiffness reduction coefficient. Then, the improved PSO algorithm is used to update the location results and accurately quantify the damage. The results of simulation and experiment show that the two-stage recognition method can identify the damage locations and detect the damage extent precisely for multi-damage and small damage, and has the advantage of good anti-noise performance.

1. Introduction

To ensure the safety and durability of large structures, the conduct of health monitoring is necessary. The basis of health monitoring is structural damage detection [1]. In recent years, the frequency and time domain-based damage identification method has been widely developed. For the problem of multi degree of freedom can not be measured for complex structure damage identification, Li (2015) et al. [2] presented a modal extension method that applies the measured modal shapes and frequencies to represent the unmeasured par. Gillich (2014) et al. [3] conducted an experimental study and finite element analysis to determine how to accurately identify the natural frequency of a structure from the vibration signal. They proposed a method that estimates the frequency range and positions the relevant signal segment by using the power spectrum of the signal component to detect the exact frequency. Wei (2015) et al. [4] studied the damage identification of thin plates and improved the existing method that used the traditional modal strain energy to identify the variation rate index, which reduced the “proximity effect” caused by damaged elements and minimized erroneous determination. Swarm intelligence algorithms such as particle swarm optimization (PSO) have been widely used in the field of damage identification owing to their fast convergence speed and simple parameter setting. Ouyang (2014) et al. [5] combined real-coded clonal selection with PSO and optimised modal frequency-based damage indicators for the damage diagnoses of hydraulic structures. Based on the quantum PSO algorithm, Gong (2015) et al. [6] proposed an objective function constructed with a generalized flexibility matrix that solve the problem of large and unstable quantitative errors of the flexibility.
matrix. Guo (2011) et al. [7] presented improvement measures for PSO, such as particle position mutation and optimal memory particle micro-search, to prevent the algorithm from falling into local optimal solutions. However, many theoretical results cannot be well applied in actual projects. Because of the uncertainty of measured structural vibration responses in an actual monitoring process, the incompleteness of the collected modal parameters, the "prematurity" of the particle swarm algorithm and the influence of random noise are the problems that restrict the application of recognition theory to practical engineering.

This paper presents a two-stage damage identification plan based on the improved PSO algorithm. In the first stage, the D-S evidence theory fusion algorithm is used to initially locate the damage. In the second stage, the improved particle swarm optimization algorithm is used to correct the location results and quantify the damage accurately.

2. Two-stage damage identification plan

(1) For the structural vibration signal, the modal translational displacement and intrinsic vibration frequency of the structure are collected before and after the damage by means of the stochastic subspace identification method.

(2) The collected translational displacement is reconstructed by the static condensation method [8], which yields the corresponding angular displacement.

(3) The first stage damage location is carried out by using the D-S evidence theory to fuse the element damage variable and element stiffness reduction factor, which are calculated from the natural frequencies and the vibration modes including the translational and corner information.

(4) The improved PSO algorithm is used to carry out the second-stage damage identification.

3. First-stage damage positioning

3.1. Modal parameter identification

The covariance-driven stochastic subspace method [9-12] was applied to identify the structural modal parameters. Based on the structural discrete state space equation model, a singular value decomposition (SVD) was conducted on the block Toeplitz matrix consisting of output covariance sequences to obtain the observable matrix and the controllable matrix. The system matrix was then given, and ultimately, the modal parameters of the system were identified.

After obtaining the system matrix, the eigenvalue decomposition was coordinated in the discrete time system model:

$$A = \Psi \Lambda \Psi^{-1}$$  \hspace{1cm} (1)

In the equation, $\Lambda = diag[\mu_i]$ is the diagonal $n$ order matrix consisting of complex of discrete time eigenvalues $\mu_i$. Matrix $\Psi$ is comprised of eigenvectors. $A$ is the state matrix of the system, and the relation between the eigenvalues and the system eigenvalues is

$$\lambda_i = \frac{\ln \mu_i}{\Delta t}$$ \hspace{1cm} (2)

In the above equation, $\lambda_i$ is the system eigenvalue, and $\Delta t$ is the sampling time interval.

The relation between the system natural frequency $\omega_i$ and system modal damping ratio $\xi_i$ can be expressed as

$$\lambda_i, \bar{\lambda}_i = -\xi_i \omega_i \pm j \omega_i \sqrt{1 - \xi_i^2}$$  \hspace{1cm} (3)

In the above equation, $j$ is the imaginary unit, $\lambda_i$ and $\bar{\lambda}_i$ are mutual conjugates.

The structure of the $i$th-order modal parameters vibration mode $\Phi_i$, damping ratio $\xi_i$ and natural frequency $f_i$ are expressed as
\[ \Phi_i = C \Psi_i, \quad \xi_i = -\frac{\lambda_i + \tilde{\lambda}_i}{2\sqrt{\lambda_i \tilde{\lambda}_i}}, \quad f_i = \frac{\sqrt{\lambda_i}}{2\pi} \]  

(4)

### 3.2. Initial damage positioning

The D-S evidence theory \[^{[13-14]}\] was applied to locate the damage. In this paper, \( D \) was assumed to be the structural damage identification derivation framework; function \( m : 2^D \rightarrow [0, 1] \), then satisfies

\[ m(D) = 1 \]  

(5)

\[ \sum_{A \subseteq D} m(A) = 1 \]  

(6)

in which \( m \) is the basic probability of framework \( D \), \( A \) is the focal element of \( m \), and \( m(A) \) is the occurrence rate of damage state \( A \).

In the structural damage identification, \( n \) information sources are set; that is, there are \( n \) sub-damage identification methods and \( k \) structural units in total. The occurrence of damage on structural element \( j \) can be identified by information source \( i \) and is \( A_{ij}(i=1,2,\ldots,n; \ j=1,2,\ldots,k) \), where \( m(A_{ij}) \) represents the probability of damage occurrence \( A_{ij} \) on element \( j \), which can be identified by means of information source \( i \).

The D-S evidence theory combination rules fuse the basic probabilities \( m(A_j) \) of every information source. The evidence theory combination rules are expressed as

\[ m(A_j) = C^{-1} \sum_{\cap j = k} \prod_{1 \leq i \leq n} m(A_{ij}) \]  

(7)

\[ C = 1 - \left| \sum_{\cap j \neq \Phi} \prod_{1 \leq i \leq n} m(A_{ij}) \right| = \left| \sum_{\cap j \neq \Phi} \prod_{1 \leq i \leq n} m(A_{ij}) \right| \]  

(8)

The damage location index used in this paper are element damage variables and element stiffness reduction factors, which give

\[ m(A_{1j}) = \frac{D_j}{\sum_{j=1}^{k} D_j} \]  

(9)

\[ m(A_{2j}) = \frac{\Delta \alpha_j}{\sum_{j=1}^{k} \Delta \alpha_j} \]  

(10)

\( D_j \) in Equation (9) is the element damage variable\[^{[15]}\] presented by Liu Hui et al., which was improved by Cao and Zhang et al.\[^{[16]}\]:

\[ D_j = \frac{EMSE_j^d - EMSE_j^u}{|EMSE_j^d - EMSE_j^u| + EMSE_j^u} \]  

(11)

In the above equation, \( EMSE_j^u = \sum_{i=1}^{m} \phi_i^T K_j \phi_i \) and \( EMSE_j^d = \sum_{i=1}^{m} \tilde{\phi}_i^T K_j \tilde{\phi}_i \) are the element strain energies before and after the damage, respectively. \( K_j \) is the stiffness matrix of element \( j \) in a
global coordinate system. $\Phi_i$ and $\tilde{\Phi}_i$ are the $i$th-order vibration modes before and after the damage, respectively.

$\Delta \alpha_j$ in Equation (10) is the element stiffness reduction factor [17]. As the structure is damaged, it is assumed in this paper that only the stiffness matrix undergoes variation, and the value is taken in $[0,1]$.

Substituting Equations (9) and (10) into Equations (7) and (8) yields

$$m(A_j) = C^{-1} \sum_{\cap_j=\Phi} m(A_{1j}) m(A_{2j})$$

$$C = 1 - \sum_{\cap_j=\Phi} m(A_{1j}) m(A_{2j}) = \sum_{\cap_j\neq\Phi} m(A_{1j}) m(A_{2j})$$

The probability of information fusion can be obtained through Equations (12) and (13). A larger value indicates that the possibility of element damage is greater.

4. Second-stage damage identification

As the damage is located by means of the D-S evidence theory fusion algorithm, the improved PSO algorithm is then applied for accurate recognition. The first stage identifies the $n$ elements that may be damaged, and the same $n$ elements then undergo the second recognition. The spatial searching dimensionality will be reduced, resulting in great improvements in convergence speed and accuracy for the PSO algorithm.

4.1. Improved PSO algorithm

The standard PSO algorithm [18] is described as

$$v_{id}^{r+1} = wv_{id}^{r} + c_1 * rand_1 * (pbest_{id}^{r} - x_{id}^{r}) + c_2 * rand_2 * (gbest_{id}^{r} - x_{id}^{r})$$

$$x_{id}^{r+1} = x_{id}^{r} + v_{id}^{r+1}$$

where $v_{id}^{r}$ and $x_{id}^{r}$ represent the dimension component $d$ of the speed and position scalars for particle $i$ at time $t$. $pbest_{id}^{r}$ and $gbest_{id}^{r}$ represent the dimension component $d$ of individual extremum and global extremum, respectively. $c_1$ and $c_2$ are learning factors; usually, $2$ is selected. $rand_1$ and $rand_2$ are random numbers in $(0,1)$. $w$ is the inertia weight. It is generally considered that a larger $w$ is advantageous to global searches and a smaller $w$ is conducive to local searches.

4.1.1. Improvement 1. The basic PSO algorithm contains the issue of prematurity [19]. Experience has shown that the population convergence speed can be varied by the inertia weight $w$. The inertia weight is usually selected using the adaptive and linear decrement methods. However, the population search is a complex nonlinear process that simply renders the linear reduction of $w$ without contributing to the global search; thus, the dynamic adjustment algorithm can be applied. In the swarm search process, the difference in fitness of each particle is quite large in the initial stage. As the iteration increases, the particle population will shift towards accuracy, and the deviation of fitness will gradually decrease. According to the concept of standard deviation in probability and statistics, the convergence maturity [20] is adopted to represent the convergence of particle swarm:

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( \frac{(f_i - \bar{f})}{\Delta f} \right)^2}$$

(15)
In the equation, \( N \) is the particle swarm size, and \( \bar{f} \) is the average fitness of all existing particles. \[ \bar{f} = \frac{1}{N} \sum_{i=1}^{N} f_i \] and \( f_i \) is the population fitness of the existing iteration. \[ \Delta f = \max_{1 \leq i \leq N} \{ f_i - \bar{f} \} \] then represents the maximum difference between the present and average fitnesses.

In the process of iteration, the dispersion of particle population fitness can be calculated by Equation (15). \( w \) is adjusted according to the value of \( \sigma \), and \( \sigma \) is in (0,1), so a boundary value of 0.5 is set in advance for \( \sigma \). If \( \sigma \) is smaller than 0.5, the convergence maturity is considered to be low, and the search may fall into a local optimum. On the contrary, if \( \sigma \) is greater than 0.5, \( w \) should be assigned a smaller value to allow a faster convergence for the group. The following formulae are used to update the inertia weight:

\[
\sigma < 0.5, \quad w' = \begin{cases} 
\frac{w_{\text{max}}}{w_{\text{max}}} \
1 - \frac{w_{\text{min}}}{w_{\text{max}}} \left( \frac{T_{\text{max}} - t}{T_{\text{max}}} \right)^2
\end{cases}
\]

\[
\sigma \geq 0.5, \quad w' = \begin{cases} 
\frac{w_{\text{max}}}{w_{\text{max}}} \left( \frac{T_{\text{max}} - t}{T_{\text{max}}} \right)^2
\end{cases}
\]

where \( w_{\text{max}} \) and \( w_{\text{min}} \) are the maximum and minimum inertia weight values, respectively, \( w_{\text{max}} = 0.9 \), and \( w_{\text{min}} = 0.4 \). \( T_{\text{max}} \) is the total number of iterations, and \( t \) is the current iteration.

4.1.2. Improvement 2. In the latter stage of the PSO algorithm, the variations of the last two items in Equation (14) are small, which means that the position of the particle varies slightly. Because the improvement to the method is undertaken to adjust the operation speed of the latter algorithm section by means of inertial weight, the position formula is revised for improvement 2. A position improvement strategy is presented in the literature [7]:

\[
x_{i'd}^{t+1} = x_{i'd}^t + v_{i'd}^{t+1} + \mu_i \ast \text{rand}_3 \ast \text{sign}(P_{c} - \text{rand}_4)
\]

where \( u \) is the particle position variation range. \( \text{rand}_3 \) is a random number in (-1,1). \( \text{rand}_4 \) is a random number in (0,1). \( P_{c} \) is the mutation probability. The selection method of the mutation probability \( P_{c} \) in this paper is adjusted according to the iteration and operation condition. If the iteration step is less than \( n \), the mutation probability is 0.01; if the iteration step is greater than \( n \) and there is no significant improvement in the adjacent second-generation \( g_{\text{best}} \), then the mutation probability increases to 0.1. Otherwise, the mutation probability remains constant, and the optimization of particles continues. \( \text{sign}(\cdot) \) is the sign function.

After this improvement, the population particles possess a certain mutation property in the search process, which will, to certain degree, prevent the particle swarm from becoming entrapped in a local optimum.

4.2. Target function improvement
The PSO algorithm requires the construction of a target function. The improvement to the target function in the literature [19] (see Equation (18)) is achieved by integrating the data on frequency, vibration mode and flexibility, and the modal assurance criterion (MAC) is applied before and after the damage to represent the correlation between the flexibility matrix and vibration mode matrix.
\[ f(x) = \sum_{i=1}^{s} \left( 1 - \text{MAC}\left( \Phi_i^e, \Phi_i^c \right) \right) + \left| \frac{w_i^d - w_i^c}{w_i^d} \right| \]

The sensitivity of the MAC criterion to damage is related to the character of the damage. If the damage is distributed such as a large area of cracked concrete, the vibration mode varies slightly. For local damage, the MAC value may be greatly reduced. On the other hand, the derivation of the expression between vibration mode and frequency observed in the literature [22] indicates that the difference in frequency squared should also be reflected by the standardized method. Because MAC values range between 0 and 1, when the correlation between the measurement frequency and the calculated frequency is high, its value should be close to 1. Therefore, the modal vibration confidence expression is modified to compensate for the drawback of low sensitivity in vibration mode when it is used alone. At the same time, issues such as the target function value, which is mostly controlled by natural frequency, can be avoided. The correction factor is

\[ \lambda = 1 + \frac{\left( w_i^c \right)^2 - \left( w_i^d \right)^2}{\left( w_i^c \right)^2 + \left( w_i^d \right)^2} \]

The flexibility modal confidence level is integrated with vibration mode confidence level to establish the target function, which is shown as follows:

\[ f = (1 - \prod_{j=1}^{s} \left| \frac{F_i^{dt} \Phi_j^e + F_i^{ct} \Phi_j^c \Phi_j^e}{F_i^{dt} \Phi_j^e \Phi_j^e + F_i^{ct} \Phi_j^c \Phi_j^c} \right|) + \frac{\left| \Phi_i^{dt} \Phi_j^{df} \Phi_j^e \Phi_j^c \right|^2}{\lambda} \]

In the equation, the flexibility matrix \( [F] = \sum_{j=1}^{s} \frac{1}{w_i^d} \{ \Phi_j \} \{ \Phi_j \}^T \), and \( (w_i^d, \Phi_i^e) \) are the frequency and vibration mode measurements under the damage condition. \( (w_i^c, \Phi_i^c) \) are the calculated frequency and vibration mode under the damage condition. \( s \) is the structural mode order.

5. Simply supported beam simulation examples

5.1. Finite element mode
The finite element model of a simply supported beam was established in ANSYS, as shown in Figure 1. The dimensions of the cross-section were as follows: length of 0.25 m, width of 0.20 m, and span length of 6 m. The elastic modulus of the material \( E = 32 \text{Gpa} \), the density \( 2500 \text{kg/m}^3 \). The beam along the span was divided into 12 equal length elements, a total of 13 nodes, which were numbered from left to right, and the unit length was 500mm.

![Figure 1. Finite element model of a simply supported beam](image)

5.2. Numerical simulation
(1) Assume the damage conditions, and simulate the damage in the form of reduction element stiffness.
(2) Apply white noise to the fourth node of the simply supported beam, and collect the acceleration response signals of the node before and after the damage.

(3) Add two types of white noise of different degrees to the acceleration response signal, with signal-to-noise ratios of 30 dB and 40 dB [21].

(4) Conduct damage identification according to the procedure described in 1.

5.3. Results and analysis
A multi-damage condition was assumed, and damage occurred in elements 4, 7, and 9 at damage levels of 10%, 30%, and 50%, respectively.

When applying the PSO algorithm, the population size was 1000. The iteration was discontinued when the fitness was lower than $10^{-4}$, and the range of position $x$ was limited to $[0,0.9]$.

The stochastic subspace method was applied to collect modal information. Due to the length limitation for this manuscript, only the vibration mode and frequency in the undamaged state and noiseless level are presented.

Table 1. The modal information of the normal operating condition

| Order | 1st Frequency 9.0129 | 2nd Frequency 36.0532 | 3rd Frequency 81.1366 |
|-------|---------------------|-----------------------|----------------------|
| Node  | Translational       | Angular               | Translational        | Angular               | Translational       | Angular               |
| 1     | 0.0000              | -0.5255               | 0.0000               | 1.0416                | 0.0000               | 1.5552                |
| 2     | -0.2597             | -0.5073               | 0.4975               | 0.9016                | 0.7016               | 1.0991                |
| 3     | -0.5014             | -0.4541               | 0.8612               | 0.5192                | 0.9916               | -0.0018               |
| 4     | -0.7086             | -0.3700               | 0.9932               | -0.0037               | 0.6991               | -1.1070               |
| 5     | -0.8673             | -0.2609               | 0.8579               | -0.5241               | -0.0070              | -1.5621               |
| 6     | -0.9666             | -0.1342               | 0.4916               | -0.9100               | -0.7102              | -1.1002               |
| 7     | -1.0000             | 0.0012                | -0.0099              | -1.0432               | -1.0000              | 0.0048                |
| 8     | -0.9655             | 0.1362                | -0.5050              | -0.8969               | -0.7053              | 1.1106                |
| 9     | -0.8654             | 0.2619                | -0.8683              | -0.5192               | 0.0021               | 1.5658                |
| 10    | -0.7065             | 0.3700                | -1.0000              | 0.0037                | 0.7078               | 1.1051                |
| 11    | -0.4995             | 0.4530                | -0.8650              | 0.5241                | 0.9996               | -0.0014               |
| 12    | -0.2586             | 0.5052                | -0.4991              | 0.9052                | 0.7065               | -1.1076               |
| 13    | 0.0000              | 0.5231                | 0.0000               | 1.0446                | 0.0000               | -1.5656               |

Table 2. The modal information of the damage condition (without noise)

| Order | 1st Frequency 8.3329 | 2nd Frequency 33.6334 | 3rd Frequency 77.8858 |
|-------|---------------------|-----------------------|----------------------|
| Node  | Translational       | Angular               | Translational        | Angular               | Translational       | Angular               |
| 1     | 0.0000              | -0.4982               | 0.0000               | 0.9975                | 0.0000               | 1.4365                |
| 2     | -0.2463             | -0.4817               | 0.4779               | 0.8723                | 0.6506               | 1.0308                |
| 3     | -0.4769             | -0.4361               | 0.8370               | 0.5350                | 0.9350               | 0.0501                |
| 4     | -0.6784             | -0.3665               | 0.9883               | 0.0500                | 0.6922               | -0.9818               |
| 5     | -0.8390             | -0.2708               | 0.8813               | -0.4689               | 0.0427               | -1.4766               |
| 6     | -0.9474             | -0.1645               | 0.5407               | -0.8599               | -0.6504              | -1.1674               |
| 7     | -1.0000             | -0.0374               | 0.0585               | -1.0281               | -1.0000              | -0.1098               |
| 8     | -0.9828             | 0.1017                | -0.4504              | -0.9742               | -0.7260              | 1.1531                |
| 9     | -0.8981             | 0.2419                | -0.8616              | -0.5962               | 0.0213               | 1.6248                |
| 10    | -0.7397             | 0.3897                | -1.0000              | 0.0613                | 0.7106               | 0.9671                |
| 11    | -0.5177             | 0.4821                | -0.8245              | 0.5740                | 0.9188               | -0.1082               |
| 12    | -0.2664             | 0.5213                | -0.4653              | 0.8505                | 0.6327               | -1.0018               |
| 13    | 0.0000              | 0.5386                | 0.0000               | 0.9708                | 0.0000               | -1.3973               |
The modal parameters in Tables 1 and 2 were used to calculate \( D_j \) and \( \Delta \alpha_j \), and PSO was then used after fusion. The stepped identification results are as follows.

Due to the length limitation for this manuscript, the subsequent identification results directly give the probability diagram and PSO quantity diagram after fusion.

It can be seen from Figure 2 to Figure 4 that under the multiple-damage condition and considering the influence of different noise level, the possible damage location can be roughly identified in the first-stage damage identification using D-S evidence theory. The three elements with larger positive
damage indicators are the damaged structural elements. However, it is possible to have a false negative at low damage element 4 and a false positive at element 8, which is near the damaged position; thus, further accurate identification is necessary. When the improved PSO method was used and elements 4, 7, 8, and 9 were selected as the elements requiring a second detection, it can be seen from the results that under the influence of different noise levels, the damage location and damage extent can be accurately identified.

For the purpose of comparison, the following three algorithms were used in the second stage identification process:

1. the standard PSO algorithm and target function (Equation (18));
2. the improved PSO algorithm and target function (Equation (18)); and
3. the improved PSO algorithm and improved target function (Equation (20)).

Every algorithm was run 10 times; see Table 3 for the calculation results. It can be seen from Table 3 that the standard PSO algorithm can basically identify the location and extent of damage, but the error is large for low-level damage. After the PSO algorithm improvement, the identification accuracy improved; the average iteration number was reduced, but mis-identification occurred at element 8. When both the improved PSO algorithm and the new target function were used, the error in the identified damage extent from the actual value was small, and the number of iterations decreased significantly.

Table 3. Average calculation results of the three methods

| Element and damage extent | 4     | 7     | 8     | 9     | Number of iterations |
|---------------------------|-------|-------|-------|-------|----------------------|
| **No noise**              |       |       |       |       |                      |
| Algorithm (1)             | 0.1923| 0.2905| 0.0484| 0.3996| 99.4                 |
| Algorithm (2)             | 0.1178| 0.2740| 0.1159| 0.4608| 85.2                 |
| Algorithm (3)             | 0.0996| 0.2760| 0.0057| 0.4749| 45.2                 |
| **SNR 30 dB**             |       |       |       |       |                      |
| Algorithm (1)             | 0.2530| 0.2834| 0.0440| 0.3581| 175.0                |
| Algorithm (2)             | 0.1367| 0.2712| 0.1863| 0.4169| 91.4                 |
| Algorithm (3)             | 0.1084| 0.2775| 0.0030| 0.4600| 44.0                 |
| **SNR 40 dB**             |       |       |       |       |                      |
| Algorithm (1)             | 0.2398| 0.3049| 0.1128| 0.3791| 162.6                |
| Algorithm (2)             | 0.1389| 0.3131| 0.0947| 0.4364| 79.4                 |
| Algorithm (3)             | 0.1040| 0.3020| 0.0291| 0.4900| 46.5                 |

6. Reinforced concrete beam experiment

6.1. Related information

The simply supported beam experiment from the literature [23] was used to verify the damage identification. The beam cross-sectional dimension was $210 \times 190 \text{mm}^2$, and the beam calculation span was 4.5 m. The tensile and compression regions were fitted with 3Φ12(HRB335) rebar and 2Φ12(HRB335) rebar, respectively; the stirrup used Φ8@225(HPB235). The protective layer thickness of the beam was 20 mm. The concrete beam was divided into 10 elements. The vibration pick-up equipment used were acceleration sensors, which were placed in the beam top center of each node (except the beam support), as shown in Figure 5.
The manual grooving method was used in the experiment to simulate beam damage; the dimensions of the groove were 20 mm×100 mm×190 mm. The locations of the three grooves were, in order, 3#, 6#, and 8#. A shock hammer was used to knock the beam, and the vibration signal after each grooving was recorded. The element stiffness reduction after grooving was 11.55%.

6.2. Results and analysis
Because the on-site environment was noisy, only those obtained data with relatively high signal-to-noise ratios were selected for structural damage recognition. The two-stage damage identification method of the multi-source information fusion-based probability method and the improved PSO algorithm were used to locate damage on the experimental simply supported beam; the identification results are shown in Figure 6 to Figure 8:

(1) Condition 1 (element 3 damaged)

(2) Condition 2 (elements 3 and 6 damaged)

(3) Condition 2 (elements 3, 6, and 8 damaged)

It can be seen from the figures above that the two-stage identification method consisting of the multi-source information fusion-based probability method and the improved PSO algorithm was able to accurately locate the damaged elements. The determination of the extent of damage in the case of multiple damages was also quite accurate.
Similarly, the identification results of the abovementioned three algorithms were compared (Table 4). The identification accuracy of standard PSO algorithm remained low; the identification result after improvement of the PSO algorithm had a certain degree of improvement but still had a 20% error from the actual value. The combination of the improved PSO algorithm with the new target function further reduced the identification error, and the calculation efficiency was quite high.

Table 4. Average calculation results from the three methods

| Condition | Element and damage extent | Number of iterations |
|-----------|---------------------------|---------------------|
|           | 3 | 6 | 7 | 8 | 9 |
| Condition 1 | Algorithm (1) | 0.0938 | — | 0.0191 | — | 0.0120 | 93.0 |
|           | Algorithm (2) | 0.1104 | — | 0.0098 | — | 0.0026 | 53.6 |
|           | Algorithm (3) | 0.1109 | — | 0.0009 | — | 0.0036 | 37.3 |
| Condition 2 | Algorithm (1) | 0.0905 | 0.1024 | 0.0312 | — | 0.0236 | 83.8 |
|           | Algorithm (2) | 0.0955 | 0.1086 | 0.0192 | — | 0.0168 | 52.0 |
|           | Algorithm (3) | 0.1105 | 0.1118 | 0.0025 | — | 0.0090 | 37.0 |
| Condition 3 | Algorithm (1) | 0.1136 | 0.1134 | 0.0120 | 0.1073 | — | 101.6 |
|           | Algorithm (2) | 0.1080 | 0.1161 | 0.0247 | 0.1025 | — | 59.8 |
|           | Algorithm (3) | 0.1129 | 0.1156 | 0.0070 | 0.1133 | — | 20.8 |

7. Conclusions

This paper has proposed a two-stage damage identification plan for a beam structure. Through numerical simulation and experimental analysis, the following conclusions have been obtained:

1) When directly using the particle swarm algorithm for damage identification, if the number of structural elements is too large, the particle dimensionality will increase. The computation efficiency is low.

2) The multi-source information fusion algorithm was used for initial identification. On that basis, the improved PSO algorithm was used for second identification. The damage can be accurately located, and the extent of damage to the damaged element can be quantified with good noise immunity.

3) The quantification error obtained when using the improved PSO algorithm and new target function is less than that obtained when using the standard PSO algorithm and traditional target function.

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