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Optimal sensor placement for health monitoring of high-rise structure based on collaborative-climb monkey algorithm

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Abstract. Optimal sensor placement (OSP) is an integral component in the design of an effective structural health monitoring (SHM) system. This paper describes the implementation of a novel collaborative-climb monkey algorithm (CMA), which combines the artificial fish swarm algorithm (AFSA) with the monkey algorithm (MA), as a strategy for the optimal placement of a predefined number of sensors. Different from the original MA, the dual-structure coding method is adopted for the representation of design variables. The collaborative-climb process that can make the full use of the monkeys' experiences to guide the movement is proposed and incorporated in the CMA to speed up the search efficiency of the algorithm. The effectiveness of the proposed algorithm is demonstrated by a numerical example with a high-rise structure. The results show that the proposed CMA algorithm can provide a robust design for sensor networks, which exhibits superior convergence characteristics when compared to the original MA using the dual-structure coding method.

Keywords: optimal sensor placement; monkey algorithm; artificial fish swarm algorithm; collaborative -climb; modal assurance criterion

1. Introduction

Large and complex high-rise structures are sometimes being placed in extreme conditions for extended periods of time in recent years (Lei *et al.* 2013a, Yi *et al.* 2013, Li *et al.* 2015). Reliable monitoring of structural responses for this type of structures has been the topic of civil engineers' research efforts (Li *et al*. 2013). Structural responses measured at specified sensor positions determine the accuracy of modal parameter identification, and are crucial in the consequent model updating, damage quantification and integrity assessment. Owing to economic reasons concerning the cost related to data acquisition and analysis, or to practical reasons such as the inaccessibility of some degrees of freedom (DOF), responses are usually recorded in a number of locations which is smaller than the total number of DOFs of the structure (Meo *et al*. 2005, Yi and Li 2012a).

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Therefore, the limited sensors that form the front end of a structural health monitoring (SHM) system should be placed in the most advantageous sites. Otherwise, incomplete modal properties will be measured and an accurate SHM assessment will be impossible. Normally, the selection is based on the previous tests and engineering judgment. In order to detect structural changes accurately, effective and efficient approaches need to be further developed (Lei *et al.* 2012b, 2013b).

Up to now, a large body of sensor placement methods has emerged, which varies in their choices of the three basic components: model, evaluation criteria, and optimization algorithm (Maul *et al*. 2008). In fact, these three aspects are intervening with each other, and the third aspect is the core one that has attracted the majority of research interest since the first two ones can be individually determined for each structure. As known, the optimal sensor placement (OSP) problem can be formulated as a single-objective optimization function involving discrete-valued variables. Conventional gradient-based optimization methods are efficient but lack of reliability in dealing with such optimization problem since convergence to the global optimum is not guaranteed (Papadimitriou *et al*. 2005). Hence, the errors between the real and estimated target modal responses obtained by sensors placed at the locations determined by these methods cannot be guaranteed to be the minimum. Keeping these things in view, attempts have been made by the engineers to devise the OSP methods employing advanced combinatorial optimization algorithms like the genetic algorithms (GAs). Yao *et al*. (1993) took the GA as an alternative to the effective independence (EfI) method and the determinant of the Fisher information matrix (FIM) was chosen as the objective function. Considering the characteristics of the OSP techniques in the large-scale spatial lattice structure, Liu *et al*. (2008) proposed some innovations to enlarge the genes storage and improve the convergence of the GA. Chow *et al.* (2010) developed a GA-based optimization method to make the entropy-based optimal sensor configuration approach applicable for large-scale structural systems. Yi *et al*. (2011b) compared the convergence properties of the GA and generalized genetic algorithm (GGA) by assessing the results of their use in sensor placement of high-rise structural health monitoring. The successful application of the GAs in the sensor network design led to the development of several other intelligent optimal algorithms. For example, Chiu and Lin (2004) defined the sensor placement problem as a min-max mathematical optimization model provided that either discrimination, or distance error, was the objective under cost and coverage constraints. Numerical experimental results showed that the simulated annealing (SA) algorithm could find the OSP under the minimum cost limitation and outperform the brute force approach no matter in the case of smaller or larger sensor fields. Rao and Anandakumar (2007) presented an improved hybrid version of the particle swarm optimization (PSO) technique by combining with the Nelder-Mead algorithm for solving the combinatorial problem of the OSP. Fidanova *et al*. (2012) proposed ant colony optimization (ACO) algorithm to solve sensor deployment problem and compared it with existing evolutionary algorithms. Experimental results verified that the ACO algorithm outperforms the other evolutionary algorithms. Minni *et al*. (2011) solved the sensor deployment problem for the simple coverage issue in the 3D terrain using the ABC algorithm where the optimal deployment position such that the required sensing range is minimum for each target to be monitored by at least one sensor node. Dutta *et al*. (2011) applied the artificial bee colony (ABC) and glowworm swarm optimization (GSO) algorithms for the integrated optimization of piezoelectric actuator and sensor placement and feedback gains. The effect of increasing the number of design variables on the optimization process showed that the ABC and GSO algorithms were robust and were good choices for the optimization of smart structures. Recently, Yi *et al.* (2012b, 2012c) incorporated the dual-structure coding method and asynchronous-climb process in the monkey algorithm (MA) and adopt it in the field of the OSP.

The purpose of this paper is to propose a new algorithm based on the original MA although a lot of algorithms have been advanced for solving the OSP problem and are widely reported in the literature. In this paper, a new hybrid algorithm called collaborative-climb monkey algorithm (CMA), which combines the artificial fish swarm algorithm (AFSA) with the MA, is proposed to solve the OSP problem in the health monitoring of high-rise structure. The rest of the paper is organized as follows: Section 2 gives a brief description of the MA. Section 3 describes the proposed CMA including its main features and implementation steps. Section 4 introduces the performance index used to optimize the sensor placement. Section 5 demonstrates the effectiveness of the proposed algorithm via a numerical simulation study for sensor deployment of a high-rise structure. Finally, conclusions are drawn in Section 6.

2. Brief description of monkey algorithm

The MA is based on the behavior of the monkeys looking for the highest mountain by climbing up from their positions (Zhao and Tang 2008). It consists of three main process namely as the climb process, watch-jump process, and somersault process, in which the climb process is employed to search the local optimal solution, the watch-jump process to look for other positions whose objective values are better than those of the current solutions so as to accelerate the monkeys' search courses, and the somersault process enable monkeys to find new searching domains. Obviously, the climb process is the main process to modify the position of the monkeys to new ones that can improve the objective function. However, in the original climb process, each monkey updates its position by choosing a new position randomly with a fixed step length without exchanging any information with other monkeys. That means the monkeys don't learn from each other and the better information obtained by some monkeys doesn't transfer to other monkeys. Namely, they don't know which choices their neighbors have found are most positive so far and how positive the best pattern of choices is. This kind of random and blind search pattern will lead to the slower convergence. In order to alleviate this problem, and also to build a much stronger search mechanism into the climb process, some improvements need to be embedded. The AFSA is inspired by the natural social behavior of fish in searching, swarming and following (Li *et al*. 2002, Shen *et al*. 2011, Tasi and Lin 2011). Searching is a basic biological behavior adopted by the fish looking for food. It is based on a random search, with a tendency toward food concentration. In order to survive and avoid hazards, the fish will naturally clustered, which called swarming behavior. Objectives common to all swarms include satisfying food intake needs, entertaining swarm members and attracting new swarm members. The following behavior means when a fish in the swarm discovers food, the others will find the food dangling after it. By analysis, it can be found that although each fish searches for the food based in its own way, better information on searching will be passed to others to guide the movement of fish effectively. Therefore, it's ideal to combine the AFSA and the climb process to improve the algorithm performance. This kind of hybrid algorithm embodies the thought of co-evolution, which can be denoted as the CMA.

3. Collaborative-climb monkey algorithm for sensor placement

3.1 Coding method and initialization

In executing the OSP searching via CMA, a general coding system for the representation of the design variables should be devised first since the original MA was designed to solve optimization problems with continuous variables while the sensor placement problem is an optimization problem involving discrete variables. Considering that the conventional real-value and binary coding methods have various kinds of drawbacks, the dual-structure coding method (Yi *et al.* 2012c) is adopted here for the representation of design variables in the CMA. Each ordered pair (x,c) represent the possible solutions of each monkey (i.e., it specifies the composition and arrangement of sensors), where x denotes the position vector in the CMA and c means the binary vector which represents the sensor's location. If the value of the jth bit position of the vector c_i is 1, it implies that a sensor is located on the jth position; and if the value of the jth bit position is 0, it means that no sensor is located on the jth position. The outline of solution representation using dual-structure coding method is given as follows:

Step (1): Suppose there be f candidate sensor positions (i.e., the total DOFs of the developed finite element (FE) model), thus the f integers from $1\sim f$ can be obtained.

Step (2): For the monkey i in the monkey population, its solution of sensor placement problem can be denoted as $xc_i=(x_i,c_i)=\{(x_{i,1},c_{i,1}), (c_{i,2},c_{i,2}),..., (x_{i,f}, c_{i,f})\}$, in which the component of the position vector x_i is the real number selected randomly from the interval [*down, up*], where $down=-5$ and $up=5$, and c_i is the binary vector which can be obtained by the follow equation

$$c_{i,j} = sig(x_{i,j}) = \frac{1}{1+e^{-x_{i,j}}} \tag{1}$$

When using Eq. (1), a judgment threshold ε should be defined first. That is, if $sig(x_{i,j})\leq\varepsilon$, then $c_{i,j}=0$; if $sig(x_{i,j})>\varepsilon$, then $c_{i,j}=1$, here $j\in\{1,2,...,f\}$. Generally, the ε can be defined as 0.5. To select the ε value most appropriately, the parametric analysis is necessary.

Step (3): Repeat *steps* (1) and (2), until M monkeys are generated (M is defined as the population size of monkeys).

Remark. What need to be mentioned is that the total number of sensors in c_i may not equal to the sensor number *sp* after random initialization. It is impractical and must be avoided. To alleviate the problem, the initial monkey population is generated by the regeneration method, i.e., going back to *step* (2).

In the following iterative process of the proposed CMA, the position vector x_i is used first; then Eq. (1) is adopted to obtain the binary vector c_i which is subsequently used to calculate the objective function value; as a consequence, each monkey will arrive at its own best position representing the personal optimal objective value $f(x_i,c_i)$ when the stopping criteria has been satisfied.

3.2 Collaborative-climb process

As aforementioned, the original climb process is a random behavior with a tendency toward the highest mountain. Keeping this problem in view, the climb process in the original MA is significantly modified by incorporate the swarming and following behaviors of the AFSA. i.e., the center position of the other monkeys can be used as the search direction of the next step when the monkey climbs at certain height, called swarming behavior; and the current optimal solution of the monkeys can be used as another search direction, called following behavior; then the monkey compares them and chooses a better one as the next search direction. Therefore, by introducing the swarming and following behaviors, the algorithm can make the full use of the monkeys' experiences to guide the movement, which embodies the thought of co-evolution and speeds up the search efficiency of the algorithm. Thus, the modified climb process can be divided three parts, which is summarized as follows:

(1) Initial climb process

For the monkey i with the position $x_i=(x_{i,1}, x_{i,2},...,x_{i,f})$, an outline of initial climb process is given as follows:

Step (1): Randomly generate integers Δx_{ij} in the interval $[-a, a]$, $j\in\{1,2,...,f\}$, and form an integer vector $\Delta x_i=(\Delta x_{i1}, \Delta x_{i2},..., \Delta x_{if})^T$, where the parameter a ($a>0$) is called the step length of the initial climb process.

Remark. The step length a plays an important role in the precision of approximation of local solution in the iteration process. Usually, the smaller the a is, the more precise the solutions are. Considering the characteristics of sensor placement problem, a can be defined as 1, 2, or another positive integer.

Step (2): Obtain monkey's new position x_{new} by $x_i+\Delta x_i$, then calculate the objective function value $f(x_{new}, c_{new})$, update the monkey's position x_i with x_{new} (update c_i with c_{new} accordingly) only if $f(x_{new}, c_{new})$ is better than $f(x_i, c_i)$, otherwise keep x_i unchanged.

Remark. It should be noted that in the *Step* (2) and the following other steps, the new components in $x_i+\Delta x_i$ may exceed the interval [*down*, *up*]. Thus, here if a new component exceeds the upper limit up, then take the component to up; if a new component below the lower limit down, then take the component to down.

Step (3): Repeat *Steps* (1) and (2) until the maximum allowable number of iterations (called the initial climb number, here denoted by *Nc*1) has been reached.

(2) Swarming behavior

For the monkey i with the position $x_i=(x_{i,1}, x_{i,2},...,x_{i,f})$, the steps of the swarming behavior are as follows:

Step (1): Calculate the center position X_{center} of the monkey population except monkey i.

Step (2): Calculate the variable j of the monkey i in the swarming behavior using the following equation

$$x_j^{jq}=\begin{cases} x_{i,j}+rand*(X_{center}(j)-x_{i,j}) & x_{i,j}\le X_{center}(j) \\ X_{center}(j)+rand*(x_{i,j}-(X_{center}(j)) & x_{i,j}>X_{center}(j) \end{cases} \tag{2}$$

Step (3): Repeat *Step* (2), until all variables of the monkey i are generated.

Swarming behavior is executed for the monkey i based on its associated X_{center} which guarantees a next position for the monkey.

(3) Following behavior

Step (1): Select the current best position X_{best} of the monkey population.

Step (2): Calculate the variable j of the monkey i in the following behavior using the following equation

$$x_j^{zw}=\begin{cases} x_{i,j}+rand*(X_{best}(j)-x_{i,j}) & x_{i,j}\le X_{best}(j) \\ X_{best}(j)+rand*(x_{i,j}-(X_{best}(j)) & x_{i,j}>X_{best}(j) \end{cases} \tag{3}$$

Step (3): Repeat *Step* (2), until all variables of the monkey i are generated.

Following behavior is executed for the monkey i based on its associated X_{best} which determines a movement towards for the monkey.

Thus, an outline of the modified climb process in the proposed CMA can be summarized as follows:

Step (1): Initialize the parameters in climb process.

Step (2): Carry out the initial climb process to obtain the monkeys' new positions.

Step (3): Calculate the x^{jq} by performing the swarming behavior for monkey population obtained in *Step* (2).

Step (4): Calculate the x^{zw} by executing the following behavior for monkey population obtained in *Step* (2).

Step (5): Evaluate the x^{jq} and x^{zw}, and then the best is selected to update the monkey's position.

Step (6): Repeat *Steps* (2)~(5) until it has implemented *Nc* generations.

3.3 Watch-jump process

After the collaborative-climb process, each monkey will look around to find the higher mountain. If a higher mountain is found, the monkey will jump there from the current position and then repeat the climb process until it reaches the top of the mountain. This process is called "watch-jump" process.

For the monkey i with the position $x_i=(x_{i,1}, x_{i,2},...,x_{i,f})$, the implementation steps of the watch-jump process is as follows:

Step (1): Randomly generate integer numbers xw_{ij} from $[x_{ij}-b, x_{ij}+b]$, $j\in\{1,2,...,f\}$, where the b is called eyesight which indicate the maximal distance that the monkey can watch, thus the new position $xw_i=(xw_{i,1}, xw_{i,2},..., xw_{i,f})^T$ can be obtained.

Remark. The eyesight b can be determined by specific situations, like the step length a, the eyesight b should also be defined as 1, 2, or other positive integer in the sensor placement problem.

Step (2): Calculate the objective function $f(xw_i, c_{new_i})$, update the monkey's position x_i with xw_i provided that $f(xw_i, c_{new_i})$ be better than $f(x_i , c_i)$, otherwise go back to *Step* (1).

3.4 Somersault process

The main purpose of somersault process is to enable monkeys to find out new searching domains. In the MA, the barycentre of all monkeys' current positions is selected as a pivot; all of the monkeys will somersault along the direction pointing to the pivot and then begins climbing again.

For the monkey i with the position $x_i=(x_{i,1}, x_{i,2},...,x_{i,f})$, the outline of the somersault process is as follows:

Step (1): Generate integer numbers θ randomly from the interval $[c,d]$ (called the somersault interval which governs the maximum distance that monkeys can somersault, which can be determined by specific situtations).

Step (2): Obtain the monkeys' pivot $p=(p_1, p_2,... p_f)^T$ by calculating the all monkeys' barycentre $p_j = \sum_i^M x_{ij} \Big/ M$, $j\in\{1,2,...,f\}$.

Step (3): Calculate $xs_{i,j}=x_{i,j}+round(\theta|p_j-x_{i,j}|)$, where the *round* denotes rounding function, update the monkeys' position with $xs_i=(xs_{i,1}, xs_{i,2},..., xs_{i,f})$ provided that the new objective values of xs_i be better than former one, and then return to the climb process; otherwise go back to *Step* (1).

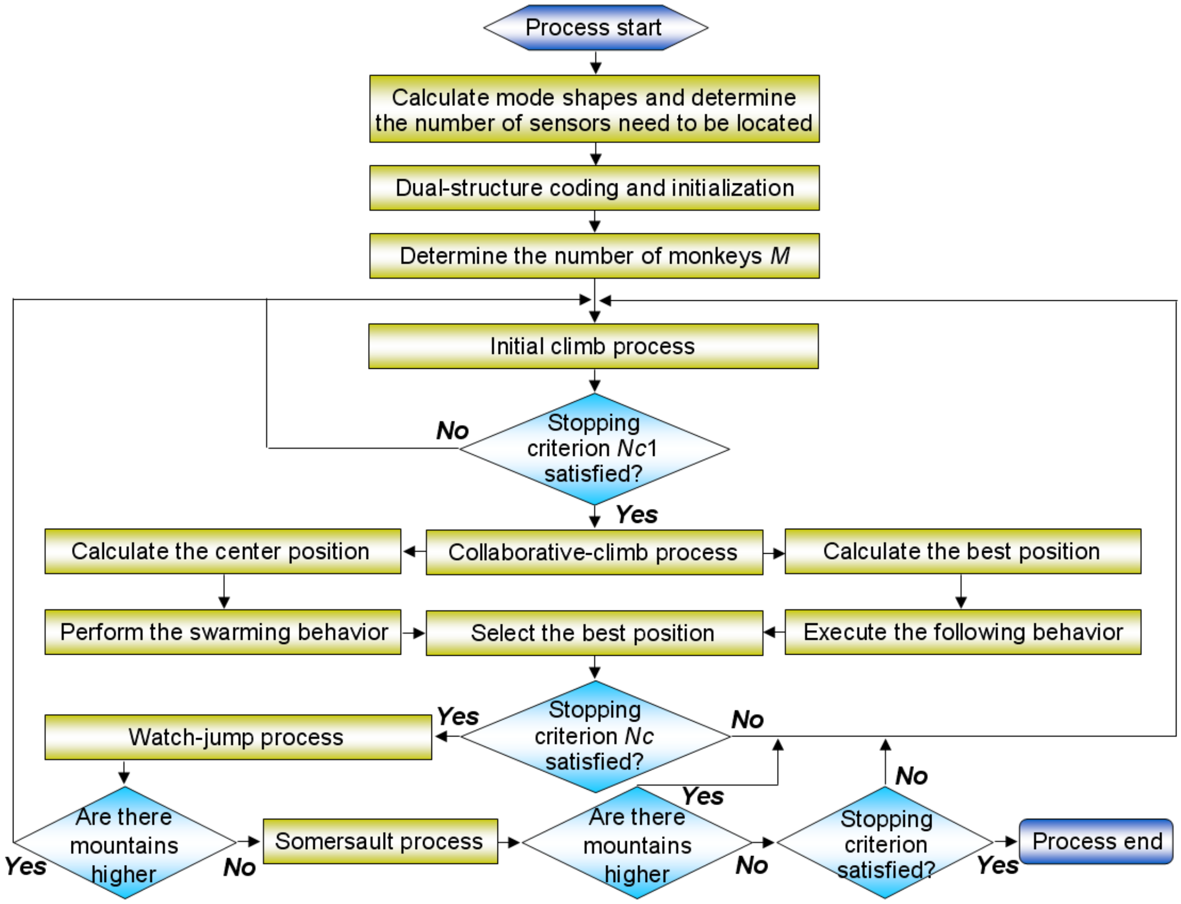


Fig. 1 Flowchart of proposed CMA for sensor placement

Fig. 1 demonstrates the whole procedure of the proposed CMA to find the optimal sensor locations presented herein. The procedure can be fully implemented easily with the high-level technical computing language MATLAB (The MathWorks, Natick, MA, USA).

4. Objective function

In the optimal sensor network under investigation the objective function is a weighting function that measures the quality and the performance of a specific sensor location design. The objective function presented herein is derived from the modal assurance criterion (MAC) (Carne and Dohmann, 1995) that measures the correlation between mode shapes.

$$\mathrm{MAC}_{ij} = \frac{(\Phi_i^T \Phi_j)^2}{(\Phi_i^T \Phi_i)(\Phi_j^T \Phi_j)} \tag{4}$$

where, Φ_i and Φ_j represent the ith and jth column vectors in the matrix Φ, respectively, and the superscript T denotes the transpose of the vector.

The MAC is designed as an ideal scalar constant relating to the relationship between two modal vectors. In Eq. (4), the element values of the MAC matrix range between 0 and 1, where zero indicates that there is little or no correlation between the off-diagonal element $\mathrm{MAC}_{ij}(i \neq j)$ (i.e., the modal vector easily distinguishable) and one denotes that there is a high degree of similarity between the modal vectors (i.e., the modal vector fairly indistinguishable). To achieve this, both sets of mode shapes have to be differentiated as much as possible. The reason for the selection of this performance index is that the MAC matrix will be diagonal for an OSP strategy, so the size of the off-diagonal elements can be defined as an indication of fitness. Thus, the objective function can be defined as follows

$$f(x,c) = \max_{i \neq j}\left\{\mathrm{MAC}_{ij}\right\} \tag{5}$$

5. Numerical case study

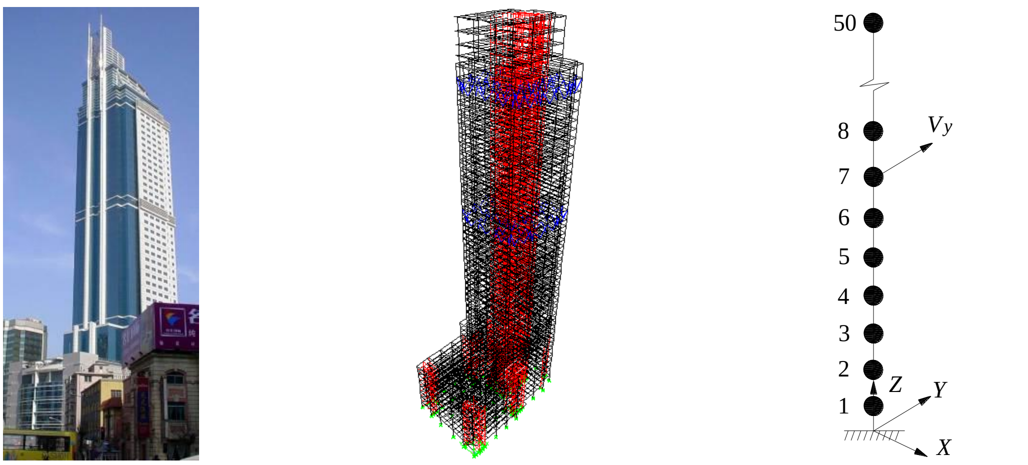
To demonstrate the possible enhancement of the proposed CMA, two cases to determine the optimal sensor network on a high-rise structure are considered.

Case 1: The original MA with the dual-structure coding (called the SMA);

Case 2: The proposed NMA.

5.1 Dalian world trade building

The Dalian World Trade Building (DWTB) located in Dalian, China, assures a place among the supertall structures in the northeast of China by virtue of its total height of 242 m. It consists of a main structure (201.9 m) and an antenna mast (40.1 m), as depicted in Fig. 3(a). It has four stories under the ground level and 50 stories above. The DWTB comprises a reinforced concrete inner



(a) Overview (b) Full-scale FE model (c) Simplified FE model

Fig. 2 The DWTB and its FE model

structure and perimeter steel frame coupled by outrigger trusses at two levels (the 30th and 45th floors). The plan of a standard floor is 37.4 m long by 38.3 m wide, and the floor-to-floor height is 3.8 m. The 15th, 30th and 45th floors are refuge floors whose height is 5.1 m.

(1) Calculation model for DWTB

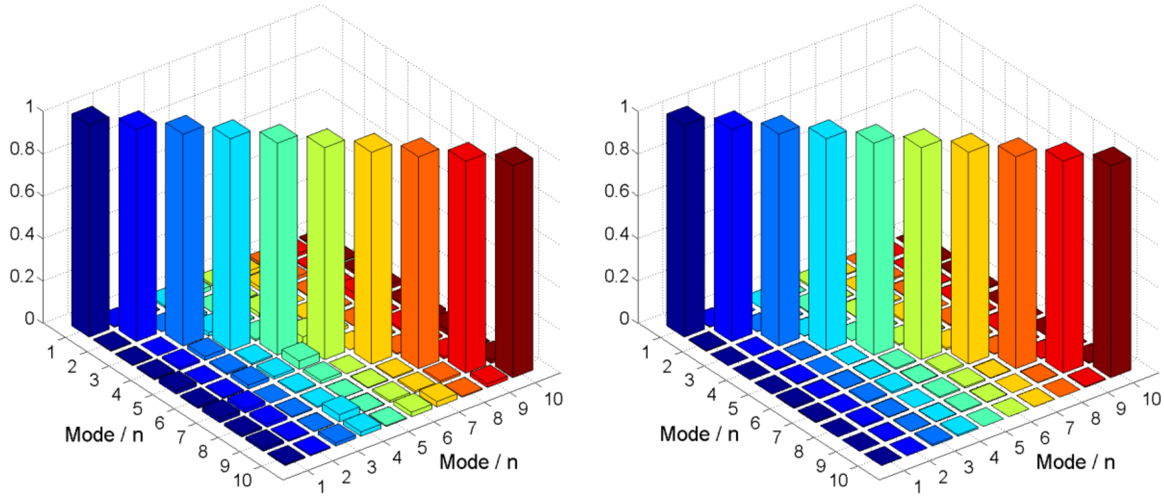
In order to accurately replicate the behavior of the real structure, a fine three-dimensional (3D) FE model should be constructed (Lei *et al*. 2012a). Based on the design drawing of the DWTB, the 3D FE model as shown in Figure 3(b) is developed by Yi *et al*. (2011a). This FE model, established with the ETABS software (Computer & Structures, Inc., Berkeley, CA, USA), consists of 13,324 node elements, 90,062 frame elements and 22,967 shell elements in total. The vibration properties were calculated by performing a modal analysis using the FE analysis code and pre/post-processor system ETABS. Here, only translational DOFs in the weak axis are considered for possible sensor placement in this case study, as rotational DOFs are usually difficult and expensive to measure. Consequently, a total of 50 DOFs are available for the sensor installation. As shown in Fig. 2(c), the nodal number increases from 1 at the fixed base to 50 at the free top end.

(2) Optimization results and discussion

To study the algorithm's solution evolution over generations under different settings of important parameters is necessary for any swarm intelligent algorithms. The important tuning parameters for the proposed CMA are the collaborative-climb process number (Nc), the initial climb number ($Nc1$), and the judgment threshold (ε). In the empirical study of the impact of three important parameters, the basic parameters of CMA remain unchanged and set as follows: a=1, b=2, the somersault interval is defined as [−3,3], and M=5. By the orthogonal experimental design, the orthogonal table can be obtained as shown in Table 1, where the numbers in brackets are level. A summary of the experimental results follows: 1) the larger Nc, the more iterations is needed for algorithm to find the optimal solution, but the higher quality is achieved. It seems that for this moderate sized problems, a typical value for Nc can be set as 100. 2) Large number of iterations in the initial climb process ($Nc1$) leads to some improvements in the quality of the solution. However, choosing too large $Nc1$ will decrease the algorithm efficiency and the climb process behaves like a pure random search, with less assistance from the historical memory. For this case, the $Nc1$ is set as 20 is reasonable. These two points verified the effectiveness of the proposed collaborative-climb method. 3) The judgment threshold ε has some impact on the improvement of

Table 1 Empirical study of the impact of different parameters on the solution quality

Scenario	Different settings of three important parameters			Objective values
	Nc	$Nc1$	ε	
1	1 (50)	1 (10)	1 (0.5)	0.0138
2	1 (50)	2 (20)	2 (0.6)	0.0183
3	1 (50)	3 (30)	3 (0.7)	0.0108
4	2 (100)	1 (10)	2 (0.6)	0.0096
5	2 (100)	2 (20)	3 (0.7)	0.0174
6	2 (100)	3 (30)	1 (0.5)	0.0120
7	3 (200)	1 (10)	3 (0.7)	0.0137
8	3 (200)	2 (20)	1 (0.5)	0.0104
9	3 (200)	3 (30)	2 (0.6)	0.0097



(a) SMA (b) CMA

Fig. 3 MAC values obtained by SMA and CMA

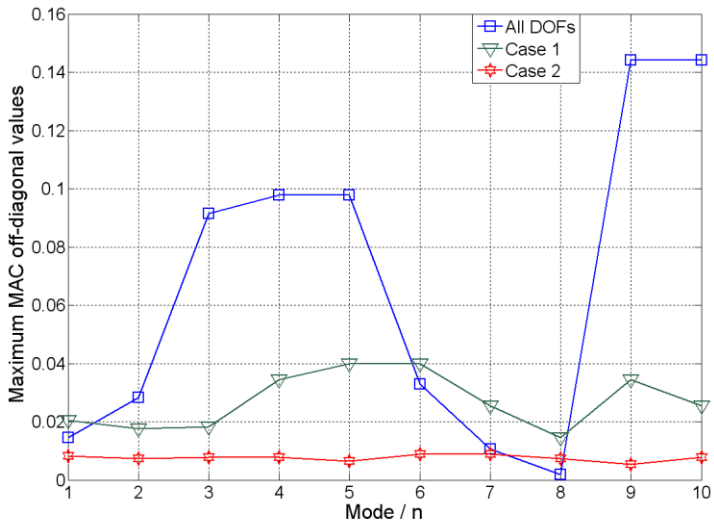


Fig. 4 Maximum MAC off-diagonal value in each of the modes

results, which confirms that the parameters need to be tuned so that the best algorithm performance can be achieved. Based on this empirical study, the judgment threshold ε can be set as 0.6.

Fig. 3 depicts the MAC values obtained by the SMA and CMA using the tuned parameters, respectively. Table 2 demonstrates the comparison of maximum MAC off-diagonal value using All DOFs, SMA and CMA. Where term “All DOFs” means the MAC matrix obtained from the full sensor set. In terms of optimization results in Fig. 3, CMA yield better sensor locations compared to the SMA. The largest off-diagonal MAC term is 0.0399 for the SMA, whereas 0.0088 for the CMA, which means the search performance of the CMA that has been effectively improved by combining the AFSA with the climb process and 77.94% reduction is gained to reach a satisfactory

Table 2 Objective function values of each kind of sensor placement scheme

Scheme selection	All DOFs	Case 1	Case 2
Objective function value	0.1442	0.0399	0.0088

Table 3 Sensor placements of the DWTB

Sensor No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
DOFs (Story)	1	3	4	5	6	8	9	12	16	17	21	25	28	31	35	36	39	42	46	48

solution. Fig. 4 demonstrate maximum MAC off-diagonal value in each of the modes obtained by the SMA and CMA. It can be easily observed that the CMA is far effective than SMA in suggesting the optimal sensor configuration. All of the maximum MAC off-diagonal values obtained by the CMA are much smaller than the SMA. What need to be mentioned is that some off-diagonal terms of the “All DOFs” in Fig. 4 are quite large compared to other algorithms, which indicates that some row vectors may be nearly a linear combination of other row vectors of the mode shape matrix specified by redundant sensors. Table 3 shows the optimal sensor configuration obtained using the proposed CMA.

6. Conclusions

Finding the optimal sensor locations is a complicated nonlinear optimization problem, and the conventional optimal methods are often difficult to alleviate the problem. This paper presents a novel hybrid algorithm called the CMA for the sensor placement. With the case study, some conclusions are summarized as follows:

- The adopted dual-structure coding method, which uses an ordered pair to stand for the possible solutions of each monkey, is an efficient coding method for the sensor placement problem.
- The proposed collaborative-climb process can make the full use of the monkeys’ experiences to guide the movement, which embodies the thought of co-evolution and speeds up the search efficiency of the algorithm.
- Numerical studies have been carried out to validate and also demonstrate the efficacy of the proposed CMA by a super high-rise structure. The results obtained showed that the convergences of the CMA using are better than those of the existing SMA, and 77.94% reduction is gained to reach a satisfactory solution.

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