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Health monitoring sensor placement optimization for Canton Tower using virus monkey algorithm

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Abstract. Placing sensors at appropriate locations is an important task in the design of an efficient structural health monitoring (SHM) system for a large-scale civil structure. In this paper, a hybrid optimization algorithm called virus monkey algorithm (VMA) based on the virus theory of evolution is proposed to seek the optimal placement of sensors. Firstly, the dual-structure coding method is adopted instead of binary coding method to code the solution. Then, the VMA is designed to incorporate two populations, a monkey population and a virus population, enabling the horizontal propagation between the monkey and virus individuals and the vertical inheritance of monkey's position information from the previous to following position. Correspondingly, the monkey population in this paper is divided into the superior and inferior monkey populations, and the virus population is divided into the serious and slight virus populations. The serious virus is used to infect the inferior monkey to make it escape from the local optima, while the slight virus is adopted to infect the superior monkey to let it find a better result in the nearby area. This kind of novel virus infection operator enables the coevolution of monkey and virus populations. Finally, the effectiveness of the proposed VMA is demonstrated by designing the sensor network of the Canton Tower, the tallest TV Tower in China. Results show that innovations in the VMA proposed in this paper can improve the convergence of algorithm compared with the original monkey algorithm (MA).

Keywords: optimal sensor placement; virus theory of evolution; virus monkey algorithm; modal assurance criterion; canton tower

1. Introduction

Due to the ever-increasing size and cost of large-scale civil infrastructures, it is vital that any anomalies from the expected deflections are detected as soon as possible, allowing remedial action to be taken, and hence trying to prevent disastrous consequences. Structural health monitoring (SHM) research represents the integration domain of these efforts striving to enhance the safety and prolong the service life of civil infrastructure (Wenzel 2009). It is well known that for an effective SHM system, many sensors have to be installed at various locations in a structure (Ko and Ni 2005). Generally, more locations of sensors placed on a structure, more detailed

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information on the stress, strain, deformation and acceleration etc., of the structure can be obtained. Advances in sensing technology have also enabled the use of large numbers of sensors for the SHM; however, more number of sensors are used, more instruments and workloads are required too. For this reason, an actual problem that should be solved by the civil engineer is how many sensors should be used and what is their optimal location yielding the desired structural response by the minimum cost. Otherwise, incomplete modal properties will be measured and an accurate structural safety assessment will be impossible.

A great deal of researches have been conducted over the last decade on the optimal sensor placement (OSP) problem using a variety of placement techniques and criteria. Among them, the most influential and commonly cited OSP method called effective independence (EfI) is developed by Kammer in 1991. In this method, Kammer argued that the optimal arrangement for measuring and estimating structural vibration was that which minimized the norm of the Fisher information matrix (FIM). Hereafter, several derivative methods based on the EfI such as the EfI-DPR (driving-point residue) were also proposed (Meo and Zumpano, 2005). Salama *et al*. (1987) proposed using modal kinetic energy (MKE) as a means of ranking the importance of candidate sensor locations. There had also been several variants on this theme, such as average kinetic energy (AKE) and weighted average kinetic energy (WAKE) proposed by Chung and Moore (1993). Li *et al*. (2007) verified that the EfI was an iterated version of MKE with re-orthonormalized mode shapes though the QR decomposition and that the latter was an iterated version of the former for the case of a structure with the equivalent identity mass matrix. With the aid of this connection, the EfI could be easily computed through row norm of the orthonormal Q matrix (Li *et al*. 2009). Lim (1992) employed the generalized Hankel matrix, a function of the system controllability and observability, to develop an approach which could determine sensor locations based on a given rank for the system observability matrix while satisfying modal test constraints. The method proposed by Stubbs (Stubbs and Park 1996) was an extension of Shannon's sampling theorem in space domain. It picked sensor positions at equidistant points for the half wavelength of the highest modes of interest. Another line of thinking similar to the space sampling method computed the roots of Chebyshev polynomials as sensor positions (Limongelli 2003). The underlying principle was that a continuous function could be approximated by the Chebyshev polynomials more exactly than other orthonormal polynomials without the Gibbs phenomenon, namely the desirable effect of minimizing the maximum error in interpolation. Different from the methods based on the FIM, Papadimitriou *et al*. (2004) introduced the information entropy norm as the measure that best corresponded to the objective of structural testing which was to minimize the uncertainty in the model parameter estimates. Moreover, Chang and Markmiller (2006), as a measurement for quantifying the reliability of a sensor network, defined the probability of detection (POD). The optimal sensor network was introduced as the network sensor configuration that could achieve the target probability of detection. For the sake of completeness, it is necessary to remark that existing approaches differ also for the solution strategies. This is not a marginal question in the OSP, especially if a large number of candidate positions have to be examined (Yi and Li 2012). As is well known, the sensor placement problem is fundamentally a constrained discrete integer optimization problem from a mathematical standpoint. The total selection pool includes $C_f^{sp} = f!/\left(f-sp\right)!sp!$ options. When the number of candidate sensors f is very large, the global optimal search for combinations of different sensor positions is prohibitive. Therefore, a systematic and efficient approach is needed to solve such a computationally demanding problem. Conventional gradient-based local optimization methods were unable to handle efficiently multiple local optima and may present difficulties in estimating the global minimum (Li *et al*. 2012). The Meta-heuristic algorithm based on the swarm intelligence is more appropriate and effective to use in such cases. For instance, the use of genetic algorithms (GAs) for the OSP was proposed by Abdullah *et al*. (2001), Guo *et al*. (2004), Liu *et al.* (2008), Roy and Chakraborty (2009), Chow *et al*. (2010), Yi *et al*. (2011a,b). In addition, the Glowworm swarm optimization (GSO) algorithm (Dutta *et al*. 2011), artificial bee colony (ABC) algorithm (Mini *et al*. 2011), Monkey algorithm (MA) (Yi *et al*. 2012a), and ant colony optimization (ACO) algorithm (Fidanova *et al*. 2012) were also applied successfully to identify the optimal sensor network. Far too many swarm intelligent optimization algorithms exist to mention them all in this paper.

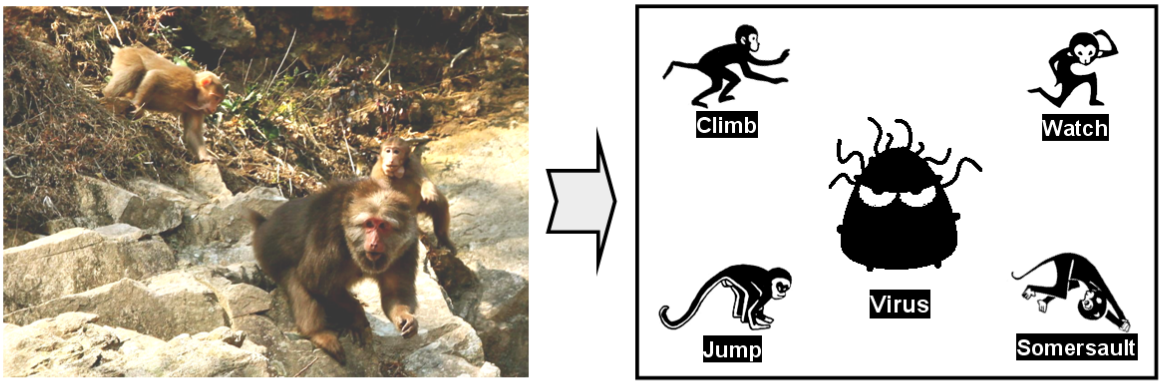
In this paper, a novel and interesting method called the virus monkey algorithm (VMA) which combined the virus evolutionary theory with the monkey algorithm (MA), is proposed to place sensors optimally on the Canton Tower, the tallest TV Tower in China, for the purpose of health monitoring. The remaining part of the paper is organized as follows. Section 2 describes the basic concepts and existing problems of the MA. Section 3 presents the main features and detailed implementation steps of the proposed VMA. The virus infection operators, that enable the coevolution of monkey population and virus population, are also defined and incorporated in this section. Section 4 gives the objective function used to optimize sensor placement. Section 5 shows the performance of this novel algorithm for the OSP in the Canton Tower. Finally, the paper is concluded in Section 6. For easy understanding, the acronyms adopted in this paper are listed in Table 1.

2. Brief description of monkey algorithm

The MA was designed by Zhao and Tang (2008) to solve global numerical optimization problems with continuous variables. The algorithm is inspired by the mountain-climb process of monkeys which mainly consists of 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 points whose objective values exceed those of the current solutions so as to accelerate the monkeys’ search courses, and the somersault process to make the monkeys transfer to new search domains rapidly. Similar to other swarm intelligent optimization algorithms, the MA has been proved to be able to solve a variety of difficult optimization problems featuring the non-linearity, non-differentiability, and high dimensionality.

Table 1 Acronyms list

SHM	Structural health monitoring
OSP	Optimal sensor placement
MA	Monkey algorithm
SMA	Original MA with the dual-structure coding
VMA	Virus monkey algorithm
DOF	Degree of freedom
FE	Finite element
MAC	Modal assurance criterion



(a) Monkey climbing the mountain (b) Monkey's characteristics

Fig. 1 Schematic drawing of the VMA

3. Virus monkey algorithm for sensor placement

It should be noticed that, despite of the MA having some attractive feature, it doesn't imply this algorithm is suitable for the OSP problems. For example, the MA was originally designed to solve optimization problems with continuous variables while the OSP was a kind of single-objective optimization problem involving discrete-valued variables. To implement the MA, it is necessary to devise a suitable coding system for the representation of design variables first. In addition, the climb process in the original MA is a pseudo gradient-based local optimization method which is unable to handle efficiently multiple local optima. Thus, for a given monkey population size, the larger the searching space, the more number of iterations needed to reach a converged solution with confidence. In other words, higher confidence usually requires the number of iterations large enough, which makes the run-time for larger candidate sensor locations prohibitive. Keeping the problem in view, the climb process in the original MA is significantly modified in this paper based on the virus theory of evolution which can shorten the computational run-time and yields better convergence performance. Fig.1 displays a schematic drawing of the proposed VMA.

3.1 Coding method and initial population

The MA is an optimization algorithm which evolves solutions in a manner analogous to the mountain-climb process of monkeys. It differs from conventional optimization techniques in that it works on encoded forms of the possible solutions. Thus, the first hurdle in setting up the OSP problem for the solution by the MA method is working out how best to encode the possible solutions as the monkey's position. Most commonly the design variables in the intelligent algorithm are coded by the binary or real value representation (Yi and Li 2012b). However, these traditional coding methods have various kinds of weakness, such as the requirement for the large storage space. In executing the sensor placement searching via the MA efficiently, the dual-structure coding method (Yi *et al*. 2012) was designed and adopted for the representation of design variables in the VMA.

Let the ordered pair (x, c) stand for the possible solutions of each monkey, where x denotes the position vector in the VMA and c means the binary vector which represents the sensor's location. Thus, an 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 degree of freedoms (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 the proposed optimization problem is denoted as $xc_i = (x_i, c_i) = \{(x_{i,1}, c_{i,1}), (x_{i,2}, c_{i,2}), ..., (x_{i,f}, c_{i,f})\}$, in which the component of 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

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

When using Eq. (1), a judgment threshold ε should be defined first. That is, if $sig(x_{i,j}) \le \varepsilon$, then $c_{i,j}$=0 (i.e., no sensor is located on this DOF); if $sig(x_{i,j}) > \varepsilon$, then $c_{i,j}$=1 (i.e., a sensor is located on this DOF), here $j \in \{1, 2, ..., f\}$. Here, the ε is defined as 0.5, thus when selecting each component of the x_i randomly from the interval $[-5, 5]$, it can be found that $0.0067 \le sig(x_i) \le 0.9933$ and $sig(0) = 0.5$ which proves that the judgment threshold given here is reasonable.

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

Remark. It has to be noted that the total number of sensors in c_i may not equal to the sensor number sp after random initialization process. It is impractical and must be avoided. Here, the initial monkey population is generated by the regeneration method when encountering this issue, i.e. going back to *step* (2).

In the following iterative process of the proposed VMA, 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 optimal objective 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 Virus-evolutionary climb process

The climb process is the main process to search the local optimal solution in the MA, which step-by-step changes the monkeys' positions from the initial positions to new ones that can make an improvement in the objective function value. As aforementioned, the climb process in the original MA is designed to use the idea of pseudo-gradient-based simultaneous perturbation stochastic approximation. This kind of climb process makes the local exploration ability of the original MA very poor since the probability of selecting a good or a bad position is the same. In order to build a much stronger intensification mechanism into the algorithm, the virus theory of evolution is incorporated in the proposed VMA to search in better local areas. The virus theory of evolution was based on the view in which virus transduction was a key mechanism for transporting segments of DNA across species (Anderson 1970). Most of viruses in nature can easily cross species barriers and are often transmitted directly from individuals of one phylum to another as horizontal propagation of genetic information. Furthermore, whole virus genomes may be incorporated into germ cells and transmitted from generation to generation as vertical inheritance. This excellent evolutionary characteristic makes the viral systems based intelligent algorithms providing successful applications to the knapsack problem, vehicle routing problem, or scheduling problems, etc. (Cortes *et al*. 2013).

Based on this theory, this section proposes the virus-evolutionary climb process, simulating the evolution like horizontal propagation between monkey and virus individuals and vertical inheritance of monkey's position information from previous to following position. The process is composed of two populations: a monkey population and a virus population. Here the monkey and virus population are defined as a set of candidate solutions and a substring set of the monkey population. As known, the healthy cells have a higher probability of developing antigenic responses (i.e., low infection probability) while the unhealthy cells with a lower probability of developing antigenic responses (i.e., high infection probability). Inspired by the performance of cells, the monkey population in this paper is divided into two subpopulations according to the average objective function value, i.e., the monkeys that have better objective function value referred to as superior monkey population, and the monkeys with the worse objective function value are called the inferior monkey population. Similarly, the virus population is also divided into two subpopulations: the serious and the slight virus populations. The serious virus is used to infect the inferior monkey to enable it to escape from the local optima, while the slight virus is adopted to infect the superior monkey to make it find a better result in the nearby area. The virus infection operators enable the coevolution of monkey population and virus population. Thus, the convergence speed is improved and premature convergence can be reduced.

(1) Virus infection operators

1) Generate the initial virus by the QR factorization

The virus individual can be considered as a kind of a monkey individual since they have the same string length. A virus individual is composed of characters 0, 1 and *, where * denotes the wildcard character which has no special meaning, and 0, 1 mean the valid characters which are the substrings of a monkey individual. For example, if the number of candidate sensors f is 10, the virus individual can be designed as $V=[*, 1, 0, *, *, *, *, 0, *, *]$. Here, it is defined that the serious virus have more valid characters while the slight virus have less. According to the matrix theory, the QR factorization of a matrix is a decomposition of the matrix into an orthogonal matrix and a triangular matrix. Suppose that the subset of candidate location corresponding to the obtained mode matrix from the FE model be Φ, $\Phi \in R^{n\times m}$, and generally $m<n$ and $r(\Phi)=m$. Thus, by the QR factorization of the matrix Φ^T, the partial positions of valid characters in the virus could be generated as follows

$$\Phi^T E = QR = Q\begin{bmatrix} R_{11} & \cdots & R_{1n} & \cdots & R_{1m} \\ & \ddots & \cdots & \cdots & \cdots \\ 0 & & R_{nn} & \cdots & R_{nm} \end{bmatrix} \tag{2}$$

where $Q \in R^{m\times m}$; $R \in R^{m\times n}$; $E \in R^{n\times n}$ and $|R_{11}| > |R_{22}| > \cdots |R_{mm}|$.

According to the above discussion, the generation procedure of virus is as follows.

Step (1): Generate $n1$ positions of valid characters in the virus by Eq. (2), then the binary vector in these positions is set to 1.

Step (2): Assuming the number of valid characters in virus be $m1$, thus the rest positions of the valid characters $m1 - n1$ can be generated randomly, and the binary vector in these positions is set to 0.

Step (3): The rest positions in virus are wildcard characters that are set to *.

2) Strength of the virus infection

A virus has a parameter, $fvirus_i$, representing the strength of the virus infection. Assume that f_i and f_i' be objective function values before and after the infection of the monkey i, respectively. The $fvirus_i$ denotes the difference between f_i and f_i', which is equal to the improvement value of the position obtained by infecting the monkey i. Thus, the set of monkey individuals which are infected by the virus can be expressed as follows

$$fvirus = \sum_{i=1}^{M1} (f_i - f_i') \tag{3}$$

where $M1$ is the virus number.

3) Virus's life force

Furthermore, each virus has a life force as follows

$$life_{i,loop+1} = decay \times life_{i,loop} + fvirus_i \tag{4}$$

where $loop$ means the number of iterations of the climb process; $decay$ denotes the life reduction rate which in the range of (0,1).

4) Procedure of the virus infection

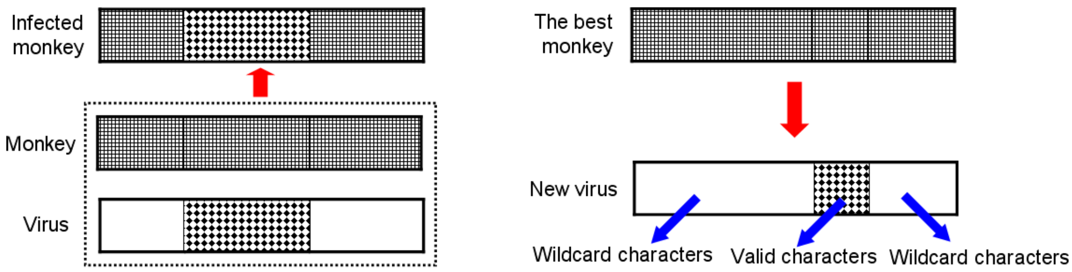
The virus infection operators in the proposed VMA are shown in Fig. 2, and the corresponding procedure is shown below:

Step (1): Overwrite a virus's substring on the string of a monkey which is selected randomly from the monkey population to generate a new monkey's position (i.e., reverse transcription operator).

Step (2): Evaluate the virus's life force. If $lifev_{loop+1} < 0$, it means that the virus individual has died and a new virus individual need to be generated by transducing partially new substring from so far the best infected monkey (i.e. transduction operator). If not, the virus individual will remain unchanged and continue to be used in the next iteration.

Step (3): Calculate the infected monkey's objective function value, replace the original monkey's position with the infected one if it has a better objective function value, otherwise keep the monkey's position unchanged.

Remark. After the virus infection operation, the adjustment strategy may need to be adopted since the total number of sensors nsp may not equal to the sensor number sp. That is to say, some substrings of c_i, that are not infected by the virus, need to be adjusted to guarantee the total number of 1 in c_i is not changed, i.e., If $nsp > sp$, replace $nsp - sp$ number 1 in c_i with 0; If $nsp < sp$, replace $sp - nsp$ number 0 in c_i with 1.



(a) Reverse transcription operator (b) Transduction operator

Fig. 2 Virus infection operators

(2) Virus-evolutionary climb steps

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

Step (1): Generate the initial virus population by the QR factorization.

Step (2): 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 a crucial role in the precision of approximation of local solution in the climb process. Usually, the smaller the parameter a is, the more precise the solutions are. Considering the characteristics of the OSP problem, a should be defined as 1, 2, or another positive integer.

Step (3): Obtain monkey's new positions x_{new1} and x_{new2} by $x_i + \Delta x_i$ and $x_i - \Delta x_i$, respectively, then calculate $f(x_{new1}, c_{new1})$ and $f(x_{new2}, c_{new2})$, update the monkey's position x_i with the better one between x_{new1} and x_{new2} (update c_i with c_{new1} or c_{new2} accordingly) only if at least one of the $f(x_{new1}, c_{new1})$ and $f(x_{new2}, c_{new2})$ is better than $f(x_i, c_i)$, otherwise keep x_i unchanged.

Remark. It has to be noted that the 'spillover' phenomenon may occur in *step* (2) and the following other steps sometimes (i.e. the new components in $x_i + \Delta x_i$ or $x_i - \Delta x_i$ 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 (4): Repeat *steps* (1) and (2) until the maximum allowable number of iterations (called the initial climb number, denoted by $Nc1$) has been reached.

Step (5): Divide the monkey population into superior (denoted as M_g) and inferior monkey populations (denoted as M_b) according to the average objective function value of monkey population.

Step (6): Carry out the virus infection procedure, and infect the inferior monkey by the serious virus while the superior monkey by the slight virus.

Step (7): Repeat *step*s (2) and (5) until the maximum allowable number of iterations (called the virus-evolutionary climb number, denoted by Nc) has been reached.

3.3 Watch-jump process

For each monkey, when it gets on the top of the mountain in the local area, it is natural to have a look and to find out whether there are other mountains around it higher than its present position. If yes, it will jump to some place of the mountain watched by it from the current position (this action is called "watch-jump process") and then repeat the climb process until it reaches the top of the mountain.

For the monkey i with the position $x_i = (x_{i,1}, x_{i,2}, ..., x_{i,f})$, the outline of the proposed 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 parameter b is a positive integer which represents the eyesight of the monkey (i.e. the maximal distance that the monkey can see), thus the new position $xw_i = (xw_{i,1}, xw_{i,2}, ..., xw_{i,f})^T$ can be obtained.

Remark. Usually, the bigger the feasible space of optimal problem is, the bigger the value of the parameter b should be taken. 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 location problem.

Step (2): Calculate the objective function $f(xw_i, c_{new_i})$, update the monkeys' 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

After repetitions of the above process, each monkey will find a locally maximal mountaintop around its initial point. In order to find a much higher mountaintop, it is natural for each monkey to somersault to a new search domain (this action is called "somersault process").

For the monkey i with the position $x_i = (x_{i,1}, x_{i,2}, ..., x_{i,f})$, the outline of the proposed 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).

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 $xs_{i,j} = x_{i,j} + round(\theta \,|\, p_j - x_{i,j} \,|)$, 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 s*tep* (1).

Fig. 3 presents the whole flowchart of the computational procedure of the proposed VMA to find the optimal sensor locations presented herein. The procedure can be fully implemented easily with the commercial software of the MATLAB (MathWorks, Natick, MA, USA).

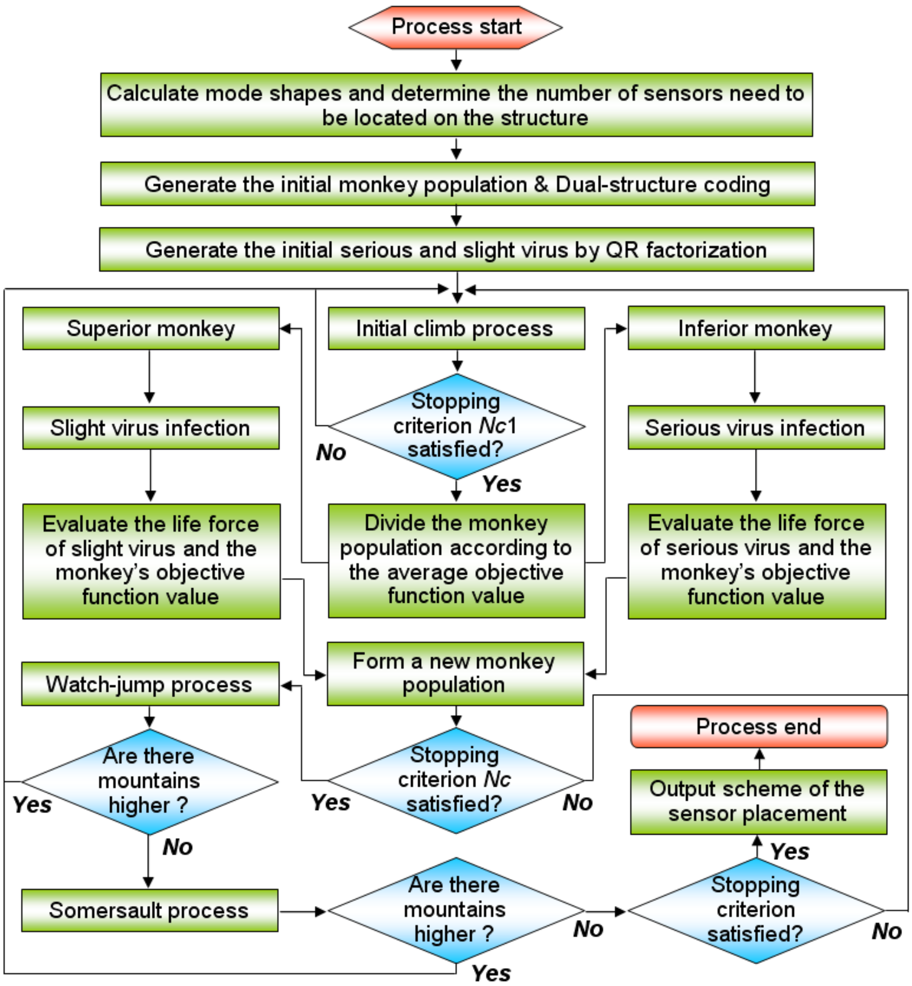


Fig. 3 Flowchart of proposed VMA for OSP

4. Objective function

In the case under investigation the objective function is a weighting function that measures the quality and the performance of a specific sensor network design. This function is maximized or minimized in the process of evolutionary optimization. The objective function presented in this paper is derived from the modal assurance criterion (MAC) (Carne and Dohmann 1995). The MAC is defined as Eq. (5), which measures the correlation between mode shapes. The element values of the MAC matrix range between 0 and 1, small maximum off-diagonal element indicates less correlation between corresponding mode shape vectors and renders the mode shapes easily distinguishable from each other, where big one denotes that there is a high degree of similarity between the modal vectors.

$$\mathrm{MAC}_{ij} = \frac{(\Phi_i^T \Phi_j)^2}{(\Phi_i^T \Phi_i)(\Phi_j^T \Phi_j)} \tag{5}$$

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

Therefore, the MAC matrix will be diagonal for an OSP strategy so the size of the off-diagonal elements can be taken as an indication of optimal result. So, the objective function can be constructed by the biggest value in all the off-diagonal elements in the MAC matrix

$$f(x,c) = \max_{i \neq j} \left\{ \mathrm{MAC}_{ij} \right\} \tag{6}$$

5. Demonstration cases

To demonstrate the effectiveness of the proposed method, a numerical case study to determine the senor configuration on the Canton Tower is considered.

5.1 Description of Canton Tower

The Canton Tower located in the city of Guangzhou, China, is a super-tall structure of 610 m high. It consists of a 454 m high main tower and a 156 m high antenna mast, as shown by Fig. 4(a). The structure comprises a reinforced concrete inner tube and a steel outer tube with concrete-filled tube columns. To maintain the safe and reliable operation of the Canton Tower, researchers from the Hong Kong Polytechnic University designed and implemented a sophisticated SHM system for it (Ni *et al.* 2009). Using this instrumented structure as a test bed, a series of SHM benchmark studies have been developed under the auspices of Asian-Pacific Network of Centers for Research in Smart Structure Technology (ANCRiSST). Among them, the benchmark study on sensor placement problem focuses on determining the OSP of accelerometers on the Canton Tower so that sufficient information about the structural behavior can be obtained.

5.2 Calculation model for Canton Tower

The OSP is important in cases where the properties of a structure, described in terms of continuous functions, need to be identified using the discrete sensor information. Thus, the optimization variables used in this paper could be the node index number. An elaborate three-dimensional FE model of the Canton Tower has been developed with the commercial software ANSYS (ANSYS, Inc., Canonsburg, PA, USA) and validated using the identified modal properties from the ambient vibration measurement (Ni *et al.* 2009). It contains 122,476 elements, 84,370 nodes, and 505,164 DOFs in total, as shown in Figs. 4(b) and 4(c). Here, the sensors examined in the model are accelerometers.

The size of the full model is too large for the SHM and related studies, therefore, a simplified model was established based on this full model with the following assumption (Ni *et al.* 2012): the floor systems are assumed as rigid body, each segment between two adjacent floors is modeled as an equivalent beam element, and the masses are lumped at the corresponding floors. Consequently, the tower is modeled as a cantilever beam with 38 nodes and 37 beam elements, i.e., 27 elements for the main tower and 10 elements for the upper mast. As shown in Fig. 5(a), the nodal number increases from 1 at the fixed base to 38 at the free top end. The vertical displacement of the structure is ignored in the reduced analytical model, giving a total of 5 DOFs for each node, i.e., two horizontal translations and three rotations. Since the rotational DOFs are usually difficult to measure in case study, a thought of taking the horizontal DOF as the master DOF and rotational DOF as the slave DOF, and reducing the slave DOF by the model reduction on the Canton Tower is implemented by Yi *et al*. (2011) [22]. In addition, according to the design drawings of the Canton Tower, it can be remarked that the main tower is made of reinforced concrete interior tube and steel external tube, while the antennary mast is made of steel, the stiffness between them is quite different. Thus, two cases are considered here, one is to retain the antenna (Fig. 5(b)), and another is completely condensation off the DOFs of the antenna (Fig.5(c)). Consequently, a total of 74 DOFs (with antennary mast $f = 74$) and 56 DOFs (without antennary mast $f = 56$) are available for the sensor installation (here $sp = 20$), and the first 10 modes of the Canton tower are selected for calculation.

5.3 Optimization results and comparison

To show the performance improvement achieved by the proposed VMA, two cases are carried out and the results are compared in details:

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

Case 2: The proposed VMA.

(a) (b) (c)

Fig. 4 The Canton Tower and its FE model: (a) Overview; (b) Full-scale FE model; (c) Model details

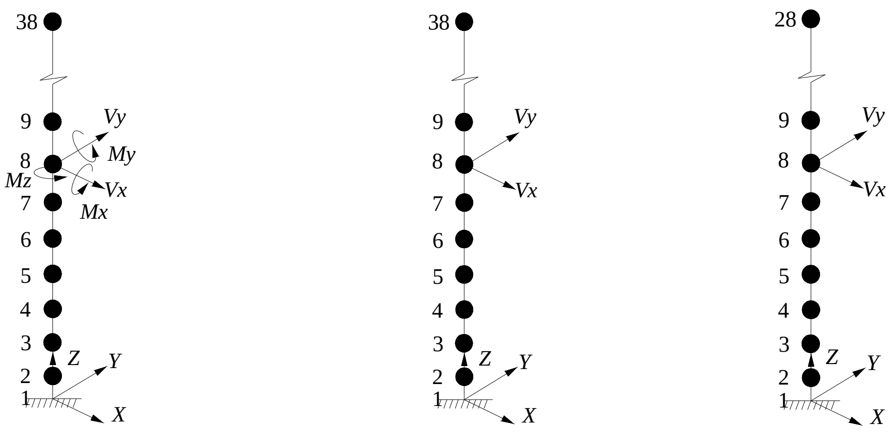


Fig. 5 Computing model for Canton Tower: (a) Simplified FE model; (b) Reduced FE model (with antennary mast); (c) Reduced FE model (without antennary mast)

(1) Sensor placement for the whole tower (with antennary mast)

Due to the nature of swarm intelligent optimization algorithms, an empirical study to determine the impacts of different VMA's important parameters on solution evolution is performed so that the best algorithm performance can be achieved. These parameters are the virus-evolutionary climb number (Nc), the initial climb number ($Nc1$), and the virus life reduction rate ($decay$). In the process of parametric analysis, the basic parameters of VMA remain unchanged and listed as follows: the monkey population size is 10, the step length a is 1, the eyesight b is 2, the somersault interval is defined as $[-3,3]$, the number of the serious and slight virus are all set to 1, the initial life force of the serious and slight virus are all set to 0, the number of valid characters of serious virus is 10 and the partial positions of valid characters generated by the QR factorization is 4, and the number of valid characters of slight virus is 5 and the partial positions of valid characters generated by the QR factorization is 2. By the orthogonal experimental design, the orthogonal table can be obtained as shown in Table 2, where the numbers in brackets are levels. In Table 2 the solution quality for different parameters is shown and some conclusions can be drawn: 1) in general, the larger the Nc the more time is needed for the algorithm to find the optimal solution, but a higher quality is usually achieved. 2) large number of iterations in the initial climb process ($Nc1$) could cause the improvement of results to some extent. However, choosing too large $Nc1$ will affect the algorithm efficiency and the VMA behaves like a pure random search, with less assistance from the virus-evolutionary. In other words, when the number of iterations is finite, increasing the $Nc1$ may deteriorate the quality of the solution. 3) The virus life reduction rate $decay$ has an obviously impact on the improvement of the solutions, which proved that the virus infection operators enable the coevolution of monkey population and virus population horizontally and vertically, therefore the convergence speed is improved evidently and premature convergence can be reduced effectively. Based on this study and the frequently used parameter values in other applications available in the literature (Anderson, 1970, Cortes *et al.* 2013), it seems that the typical values here can be set as $Nc = 200$, $Nc1 = 10$, and $decay$=0.8, respectively.

Table 2 Empirical study of the impact of different parameters on the solution quality

Scenario	Different settings of three important parameters			Objective values
	Nc	*Nc*1	*decay*	
1	1 (50)	1 (10)	1 (0.4)	0.5173
2	1 (50)	2 (20)	2 (0.6)	0.5313
3	1 (50)	3 (40)	3 (0.8)	0.5246
4	2 (100)	1 (10)	2 (0.6)	0.5329
5	2 (100)	2 (20)	3 (0.8)	0.5145
6	2 (100)	3 (40)	1 (0.4)	0.5180
7	3 (200)	1 (10)	3 (0.8)	0.5084
8	3 (200)	2 (20)	1 (0.4)	0.5115
9	3 (200)	3 (40)	2 (0.6)	0.5095

Table 3 Objective function values of each kind of sensor placement scheme

Scheme selection	All DOFs	Case 1	Case 2
Objective function value	0.9694	0.6446	0.5084

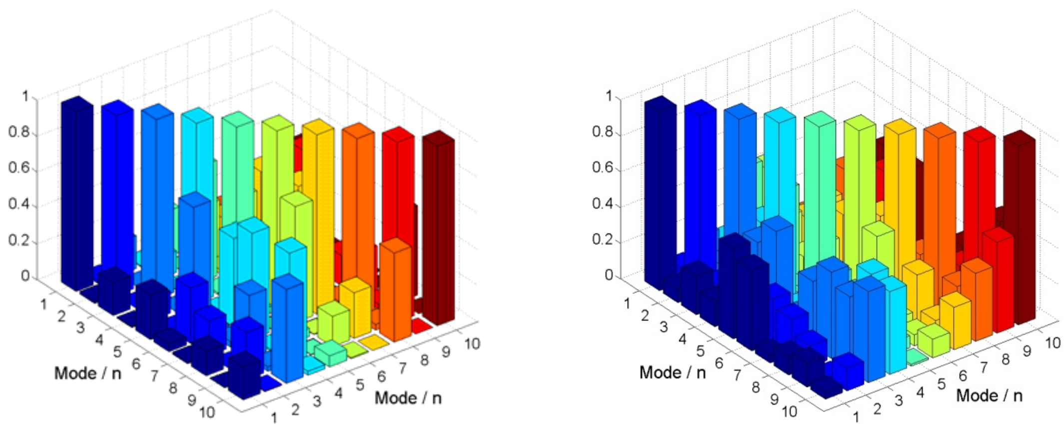
Table 4 Sensor placement result of the Canton Tower determined by the VMA

Sensor number		1	2	3	4	5	6	7	8	9	10
Nodes	*X* direction	2	/	3	4	/	/	14	/	/	20
	Y direction	/	2	/	/	6	8	/	16	19	/
Sensor number		11	12	13	14	15	16	17	18	19	20
Nodes	*X* direction	/	21	/	22	/	23	24	/	25	29
	Y direction	20	/	21	/	22	/	/	24	/	/

Fig. 6 depicts the MAC values obtained by the SMA and the VMA. Comparing Figs. 6(a) and 6(b), it can be noted that the viral system approach outperforms the SMA practically in every configuration except mode one although the trend and the values of the two algorithms seems identical. In order to highlight the effectiveness of the proposed algorithm, maximum MAC off-diagonal value in each of the modes is illustrated in Fig. 7. The Fig. 7 confirms that the proposed VMA is far superior to the SMA implementations in finding the optimal sensor locations. Except mode one, all of the maximum MAC off-diagonal values obtained by the VMA are much smaller than other algorithms. A close look at the results presented in Fig. 7 has shown that the off-diagonal terms of the “All DOFs” (i.e., all nodes have the sensor) are fairly large compared with other methods. This phenomenon clearly indicates that the row vector of the mode shape matrix specified at the some sensor position may conflict with other ones. Namely, this row vector is nearly a linear combination of other row vectors of the mode shape matrix specified by previous sensors. Table 3 shows the objective function values obtained by different methods. From Table 3, it is observed that the largest off-diagonal MAC term is 0.6446 for the SMA, whereas 0.5084 for the VMA, that means the search capabilities of the VMA have been effectively improved by adopting the virus infection operators and 21.2% reduction is gained to reach a satisfactory solution. Table 4 presents the optimal sensor locations obtained using the proposed VMA.

2) Sensor placement for the main tower (without antennary mast)

In order to find out the most appropriate parameters of the VMA for the main tower, a number of empirical studies were carried out in the same way. The results are listed in Table 5. Similar to the earlier study, it can be observed that effects of variation of the three important parameters on the solution quality are different. As expected, the virus life reduction rate *decay* can leads to significant improvements of the solutions. Thus, three important parameters of VMA were calibrated to the following values after testing and trying with different combinations: $Nc = 50$, $Nc1 = 20$ and $decay$=0.6. The other basic parameters of VMA remain unchanged.



(a) SMA (b) VMA

Fig. 6 MAC values obtained by SMA and VMA

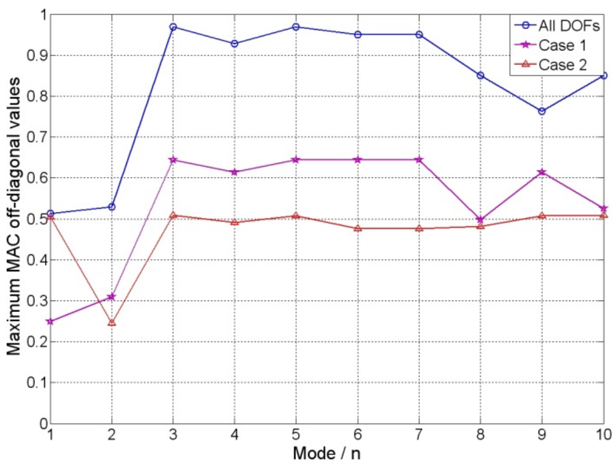
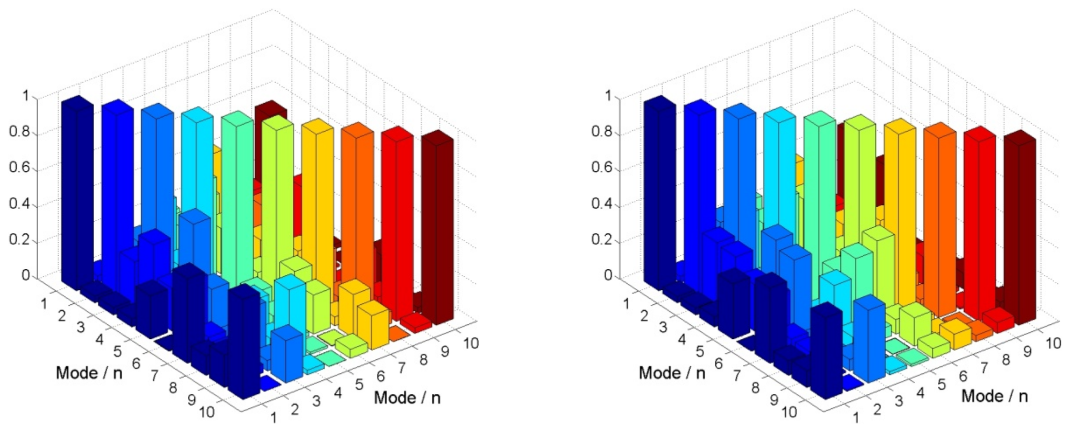


Fig. 7 Maximum MAC off-diagonal value in each of the modes

Table 5 Empirical study of the impact of different parameters on the solution quality

Scenario	Different settings of three important parameters			Objective values
	Nc	*Nc*1	*decay*	
1	1 (50)	1 (10)	1 (0.4)	0.4807
2	1 (50)	2 (20)	2 (0.6)	0.4590
3	1 (50)	3 (40)	3 (0.8)	0.4699
4	2 (100)	1 (10)	2 (0.6)	0.4604
5	2 (100)	2 (20)	3 (0.8)	0.4682
6	2 (100)	3 (40)	1 (0.4)	0.4628
7	3 (200)	1 (10)	3 (0.8)	0.4589
8	3 (200)	2 (20)	1 (0.4)	0.4590
9	3 (200)	3 (40)	2 (0.6)	0.4565

In Fig. 8, the overall behavior of the MAC values obtained by the SMA and VMA are shown, respectively. Further to demonstrate the effectiveness of the improvements of the VMA, another diagram is plotted and compared as shown in Fig. 9. It is obvious that the computational performance of the proposed VMA is far superior when compared to the other algorithm although three results are mixed together. Most of the maximum MAC off-diagonal values in Fig. 9 obtained by the VMA are smaller than values obtained by the SMA. This can be further verified from Table 6. Through the VMA, the obtained objective function values can improve the performance by 17.8% and 46.5% when compared to the SMA and All DOFs, respectively. Table 7 demonstrates the optimal sensor locations for the main tower obtained using the VMA. This study clearly indicates that it is desirable to employ the virus infection operators in the MA in order to yields better convergence performance.



(a) SMA (b) VMA

Fig. 8 MAC values obtained by SMA and VMA

Table 6 Objective function values of each kind of sensor placement scheme

Scheme selection	All DOFs	Case 1	Case 2
Objective function value	0.8579	0.5581	0.4590

Table 7 Sensor placements of the Canton Tower determined by the VMA

Sensor number		1	2	3	4	5	6	7	8	9	10
Nodes	*X* direction	/	2	/	3	/	/	5	/	9	/
	Y direction	1	/	2	/	3	4	/	6	/	9
Sensor number		11	12	13	14	15	16	17	18	19	20
Nodes	*X* direction	12	13	15	/	/	19	/	22	23	/
	Y direction	/	/	/	15	17	/	20	/	/	24

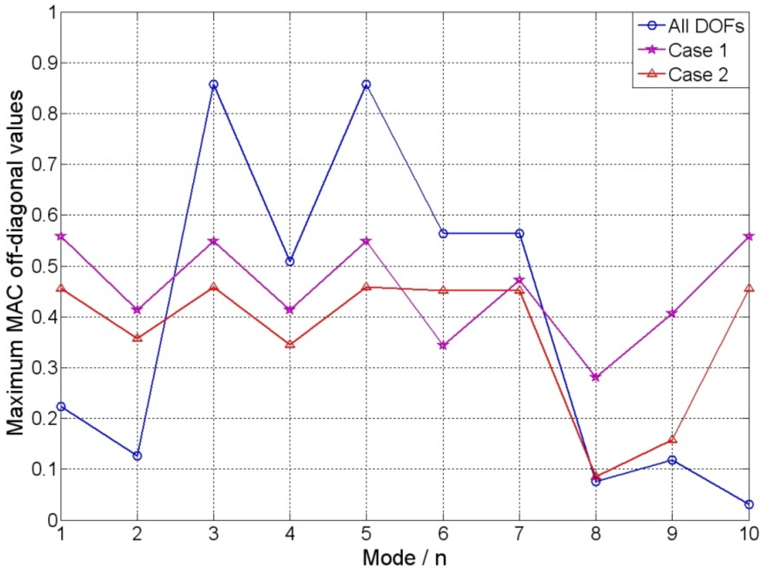


Fig. 9 Maximum MAC off-diagonal value in each of the modes

6. Conclusions

This paper presents a novel bio-inspired algorithm called the viral monkey algorithm (VMA) to the sensor problem for modal identification purposes. Numerical studies have been carried out to validate and also demonstrate the efficacy of the proposed VMA on the Canton Tower. The following are some of the conclusions.

- Inspired by the performance of cells, the monkey population in this paper is divided into the superior and the inferior monkey population. Similarly, the virus population is also divided into two subpopulations: the serious and the slight virus populations. The serious virus is used to infect the inferior monkey to enable it to escape from the local optima, while the slight virus is adopted to infect the superior monkey to make it find a better result in the nearby area. This kind of novel virus infection operators enables the coevolution of monkey population and virus population, therefore the algorithm performance is effectively improved.
- Numerical studies have been carried out to assess and also demonstrate the efficacy of the proposed VMA by considering the Canton Tower with or without the antenna mast. The comparison results have showed the better performance of the VMA compared to the SMA both in terms of generating optimal solutions as well as faster convergence. In total, about 20% reduction is gained to reach a satisfactory solution.
- The idea of the VMA not only can be applied to tackle the sensor placement problem, but also can be applied to other combinatorial optimization problems, such as traveling salesman and knapsack problems. Compared with the commonly used sensor placement methodologies, the main disadvantage of the VMA is its computational complexity and multiple parameters. Fortunately, these problems can be easily overcome by the parameter empirical study using the MATLAB software.

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