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Damage detection based on improved particle swarm optimization using vibration data

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ABSTRACT

An immunity enhanced particle swarm optimization (IEPSO) algorithm, which combines particle swarm optimization (PSO) with the artificial immune system, is proposed for damage detection of structures. Some immune mechanisms, selection, receptor editing and vaccination are introduced into the basic PSO to improve its performance. The objective function for damage detection is based on vibration data, such as natural frequencies and mode shapes. The feasibility and efficiency of IEPSO are compared with the basic PSO, a differential evolution algorithm and a real-coded genetic algorithm on two examples. Results show that the proposed strategy is efficient on determining the sites and the extents of structure damages.

1. Introduction

In the last few decades, techniques based on vibration responses have been widely used for damage identification and structural health monitoring. The premise for these techniques is that damage causes a change in structural physical properties, mainly in stiffness and damping at the damaged locations. The associated changes in the structure will result in changes in the natural frequencies, mode shapes, damping ratios, modal strain energies, or other dynamic characteristics of the system. Therefore, monitoring one or more of these properties of the damaged structure, the location and extent could be identified. Extensive literature reviews on vibration-based damage detection techniques have previously been reported [1,2]. Numerous damage indicators have previously been adopted, including natural frequency [3,4], mode shape [5], modal flexibility [6], correlation of modal data [7], etc.

The usual model-based damage detection methods minimize an objective function, which is defined in terms of the discrepancies between the vibration data identified by modal testing and those computed from the analytical model. However, conventional optimization methods are gradient based and usually lead to a local minimum only [8]. A global optimization technique is needed to obtain a more accurate and reliable solution. In recent years, genetic algorithm (GA) as a global optimization method has been applied to damage detection problems [3,8–11], and promising results are obtained. Some hybrid methods of GA and other techniques were also proposed for damage detection. He and Hwang [12] proposed an adaptive real-parameter simulated annealing genetic algorithm for damage detection and was demonstrated by beam-type structures. Sahoo and Maity [13] adopted a hybrid neural genetic algorithm for damage assessment based on the fact that the damage has an important effect on the static as well as dynamic behavior of the structure. Kokot and Zembaty [14] developed a damage reconstruction method of 3D frames based on genetic algorithm and Levenberg–Marquardt local search.

Particle swarm optimization (PSO) [15–17] is a novel population-based global optimization technique developed recently. Although PSO shares many similarities with genetic algorithms, the standard PSO does not use general genetic operators. PSO has received wide attentions from the optimization community due to its simplicity, wide applicability and outstanding performance. Except to theoretical studies, it has been adopted to solve various real-world optimization problems [18–20]. As compared to GA and several other optimization algorithms PSO is more efficient, requiring fewer number of function evaluations, while leading to better or the same quality of results on function optimization [21–23] and engineering problems [24–26]. The study of Lee et al. [26] also shows that PSO is more efficient than GA on high dimensional problems. Similar to other evolutionary algorithms, PSO also has the problems of premature convergence and taking a long time to locate the exact local optimum within the region of convergence. Therefore some variants of PSO were proposed to improve the performance. Chen and Zhao [27] proposed a PSO with adaptive population size to enhance the overall

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performance of PSO. Chen et al. [28] proposed a hybrid algorithm that combines the exploration ability of PSO with the exploitation ability of extremal optimization. Nickabadi et al. [29] proposed a novel PSO with adaptive inertia weight. Sabat et al. [30] proposed an integrated learning PSO to enhance the convergence and quality of solution.

In this paper, PSO is applied to damage detection of engineering structures. Meanwhile, to improve the convergence speed and accuracy, several immune mechanisms, selection, receptor editing and vaccination, are incorporated into PSO and an immunity enhanced particle swarm optimization (IEPSO) algorithm is proposed. Such hybrids have been successfully applied to global optimization of numerical functions [28,31] and have been used to solve various engineering problems [31,32]. To verify the performance of the proposed methodology on damage detection, a simply supported beam and a truss structure are taken as numerical examples. IEPSO is also compared with the basic PSO, a differential evolution (DE) [33–35] algorithm and a real-coded genetic algorithm (RCGA). Results show that, PSO and DE are more powerful optimization tools than RCGA and IEPSO is the most efficient algorithm for damage detection.

The remainder of this paper is organized as follows. In Section 2, the mathematical model for vibration-based damage detection is described. In Section 3, the original PSO is introduced. In Section 4, the proposed IEPSO is described. In Section 5, numerical studies are presented, and in Section 6, conclusions are provided.

2. Mathematical model for vibration-based damage detection

2.1. Parameterization of damage

The modal characteristics of an undamaged structure are described by the eigenvalue equation:

$$\boldsymbol{K}\boldsymbol{\phi}_i - \omega_i^2 \boldsymbol{M}\boldsymbol{\phi}_i = 0, \tag{1}$$

where $\boldsymbol{K}$ is the structural stiffness matrix, $\boldsymbol{M}$ is the mass matrix, ω_i is the ith natural frequency and $\boldsymbol{\phi}_i$ is the corresponding mode shape.

According to continuum damage mechanics, damage can be quantified through a scalar variable d whose values are between 0 and 1 [36]. A 0 value corresponds to no damage while values next to 1 imply a rupture. In the context of discretized finite elements, damage can be represented by a decrease in the stiffness of the individual elements as

$$\boldsymbol{k}_d^e = \boldsymbol{k}^e(1 - d_e), \tag{2}$$

where $\boldsymbol{k}^e$ and $\boldsymbol{k}_d^e$ are the eth element stiffness matrices of the undamaged and damaged structures, respectively; d_e is the damage index of the eth element.

2.2. Objective function based on vibration data

The observation that changes in structural properties cause changes in vibration frequencies and mode shapes is the impetus for using modal methods for damage identification and health monitoring. The objective function based on both natural frequency and mode shape changes can be expressed as

$$f = \sum_{i=1}^{NF} w_{\omega i}^2 \left(\frac{\omega_{e,i} - \omega_{n,i}}{\omega_{n,i}} \right)^2 + \sum_{j=1}^{NM} w_{\phi i}^2 \sum_{k=1}^{NP} \left(\frac{\phi_{e,ij} - \phi_{n,ij}}{\phi_{n,ij}} \right)^2, \tag{3}$$

where $w_{\omega i}$ is a weight factor of the output error of the ith natural frequency, $w_{\phi j}$ is a weight factor of the output error of the jth mode shape, $\omega_{e,i}$ is the ith experimental natural frequency, $\omega_{n,i}$ is the ith numerical natural frequency, $\phi_{e,jk}$ is the experimental modal displacement of the kth point of the jth mode shape, $\phi_{n,jk}$ is the numerical modal displacement of the kth point of the jth mode shape, and NF, NM and NP are the number of natural frequencies, number of mode shapes and number of measured points of modal displacement. Changes of modal displacements and natural frequencies are normalized to get a better representation of the relative change in response.

The solution space is the space of damage indices corresponding to each finite element and the goal of optimization is to force the damage indices corresponding to each finite element to match the "true" damage indices of the numerical model given a particular damage condition.

3. Particle swarm optimization

Inspired by a model of social interactions between independent animals seeking for food, PSO utilizes swarm intelligence to achieve the goal of optimization. Instead of using genetic operators to manipulate the individuals, each individual in PSO flies in the search space with a velocity which is dynamically adjusted according to its own flying experience and flying experience of its companions. Each individual is treated as a volume-less particle (a point) in the D-dimensional search space. The ith particle is represented as $\boldsymbol{x}_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$ in the D-dimensional space, where $x_{ij} \in [l_j, u_j], j \in [1, D]$, l_j and u_j are the lower and upper bounds of dimension j. The best previous position of the ith particle is recorded as $\boldsymbol{p}_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$. The best particle among all the particles is represented as $\boldsymbol{p}_g$. The velocity for particle i is represented as $\boldsymbol{v}_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$, which is clamped to a maximum velocity $V_{\max}$. In each generation t, the particles are manipulated according to the following equations:

$$\boldsymbol{v}_i(t+1) = \boldsymbol{v}_i(t) + r_1 c_1(\boldsymbol{p}_i(t) - \boldsymbol{x}_i(t)) + r_2 c_2(\boldsymbol{p}_g(t) - \boldsymbol{x}_i(t)), \tag{4}$$

$$\boldsymbol{x}_i(t+1) = \boldsymbol{x}_i(t) + \boldsymbol{v}_i(t+1), \tag{5}$$

where c_1 and c_2 are two positive constants, which control how far a particle will move in a single iteration; r_1 and r_2 are random values in the range [0,1].

Shi and Eberhart [37] later introduced inertia term w term by modifying (1) to

$$\boldsymbol{v}_i(t+1) = w\boldsymbol{v}_i(t) + r_1 c_1(\boldsymbol{p}_i(t) - \boldsymbol{x}_i(t)) + r_2 c_2(\boldsymbol{p}_g(t) - \boldsymbol{x}_i(t)), \tag{6}$$

They proposed that suitable selection of w will provide a balance between global and local explorations, thus requiring less iterations on average to find a sufficiently optimal solution. As originally developed, w often decrease linearly from about 0.9 to 0.4 according to the following equation:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{T} \times t, \tag{7}$$

where $w_{\max}$ and $w_{\min}$ are the initial weight and final weight, respectively, T is the maximum number of allowable generations.

Four types of boundary conditions, namely, absorbing, reflecting, invisible, and damping, have been reported in literature [38]. We found a damping boundary is adequate for general problems. As for damage detection problem, generally only few elements are damaged, and most elements are still intact. The parameter values of these intact elements are always in the upper bound [12]. In order to avoid oscillating around the upper boundary and to quickly return to the feasible region around the lower boundary, the following boundary condition is adopted:

$$x_{id} = \begin{cases} 2 \cdot l_d - x_{id} & x_{id} < l_d \\ u_d & x_{id} > u_d \end{cases}, \tag{8}$$

$$v_{id} = -rand() \cdot v_{id} \quad x_{id} < l_d \ \text{ or } \ x_{id} > u_d, \tag{9}$$

where $rand()$ is a random number in the range [0,1].