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# AN OUTPUT-ONLY DAMAGE IDENTIFICATION METHOD BASED ON REINFORCEMENT-AIDED EVOLUTIONARY ALGORITHM AND BAYESIAN INFERENCE REGULARIZATION WITH HETEROGENEOUS DATA FUSION

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**Abstract.** The absence of excitation measurements may pose a huge challenge in the application of many damage identification methods since it is difficult to acquire the external excitations, such as wind load, traffic load. To deal with this issue, a novel output-only structural damage identification approach based on reinforcement-aided evolutionary algorithm and heterogeneous response reconstruction with Bayesian inference regularization is developed. On the one hand, heterogeneous measurements (e.g., displacements, strains, accelerations) are rescaled and reconstructed with the aid of Bayesian inference regularization technique. Structural damages are identified by minimizing the discrepancies between the measured and reconstructed responses. On the other hand, to solve the optimization-based inverse problem, a reinforcement-aided evolutionary algorithm, named Q-learning hybrid evolutionary algorithm, integrating Jaya algorithm, differential algorithm and Q-learning algorithm is proposed as a search tool. To validate the feasibility and applicability of the

proposed method, laboratory tests on a five-story steel frame structure are carried out. It is shown that both the locations and extents of the damaged elements can be accurately identified by the proposed method without the information of input force.

## 1 INTRODUCTION

In recent years, many investigators have reported the use of response reconstruction technique for the identification of structural damage, and fruitful results have been achieved. Zhang and Xu[1] presented a response reconstruction method by Kalman filter for damage identification under unknown external excitation.

Nevertheless, most of the output-only methods for damage identification problem in the present literature only use a single type of measurement. From the practical point of view, nowadays, multi-type sensors, such as displacement transducers, strain gauges, accelerometers are widely employed in the structural health monitoring systems of large-scale civil structures. Some studies have reported that making full use of heterogeneous responses can enhance the accuracy and reliability of damage detection[2]. For example, Lu et al. proposed a damage detection scheme through data fusion of accelerometers and strain responses, and the results showed the superiority of hybrid sensor measurement[3]. Zhang and Xu[4] presented a multi-sensing damage identification method via response reconstruction, and verified the effectiveness of the proposed method with laboratory tests on a simply supported overhanging beam. Jeong et al. applied hybrid acceleration and angular velocity to successfully identify damages of monopile offshore wind turbine structures[5]. Wang et al. developed a damage detection method based on the cross-correlation function among acceleration and strain data[6]. Based on these previous studies, it is found that different types of sensors, accelerometers, strain gauges, and displacement transducers, etc., have their own merits and drawbacks. Therefore, heterogeneous response reconstruction is suggested for output-only damage identification.

The contribution of the present paper is that an output-only structural damage identification based on QHEA and heterogeneous response reconstruction with Bayesian inference regularization is proposed, to deal with the problem of the absence of excitation measurements. First, heterogeneous response reconstruction technique is derived considering the complementary benefits of multi-type sensors. Additionally, to solve the ill-posed problem in response reconstruction owing to the presence of measurement noise, Bayesian inference regularization is adopted, and the drifted estimation of structural responses can be properly addressed. Moreover, to optimize the objective function established based on the measured and reconstructed responses, a new reinforcement-aided evolutionary algorithm QHEA is proposed by integrating the Jaya, DE and Q-learning algorithms. Finally, experimental validations on a five-floor steel frame structure are conducted to demonstrate the applicability of the proposed method.

## 2 HETEROGENEOUS RESPONSE RECONSTRUCTION

### 2.1 Response reconstruction in time domain

The equation of motion of a linear structural system subjected to external input force can be expressed as follows

$$M\ddot{u}(t)+C\dot{u}(t)+Ku(t)=Bf(t) \tag{1}$$

where are $\ddot{u}(t)$, $\dot{u}(t)$, $u(t)$ stand for the vectors of acceleration, velocity and displacement responses, respectively; *M*, *C*, *K* are the mass, damping, stiffness matrices; $f(t)$ means the time-dependent external excitation and *B* denotes the mapping matrix with the value of 1 relating the force location.

Rayleigh damping model is adopted as follows

$$C=aM+bK,\quad \zeta_r=\frac{a}{2\omega_r}+\frac{b\omega_r}{2} \tag{2}$$

where *a* and *b* represent the damping coefficients and they can be determined by modal damping ratio $\zeta_r$ and natural frequencies $\omega_r$.

For a structure under the unit impulse excitation, the motion equation can be written as

$$M\ddot{h}(t)+C\dot{h}(t)+Kh(t)=B\delta(t) \tag{3}$$

where $\delta(t)$ is the Dirac delta function. The impulse response function is able to be represented as a free vibration state with the specific initial conditions. Assuming the structural system is initially in static equilibrium, the unit impulse response function can be calculated by numerical integration methods, for example, Newmark-*β* method

$$\begin{cases} M\ddot{h}(t)+C\dot{h}(t)+Kh(t)=0 \\ h(0)=0,\dot{h}(0)=M^{-1}B \end{cases} \tag{4}$$

where $h(t)$, $\dot{h}(t)$, $\ddot{h}(t)$ are the unit impulse displacement, velocity, acceleration vectors in the time domain, respectively.

The strain responses $\varepsilon_q(t_n)$ at the location *q* with local co-ordinates (x, y) in a typical Euler beam element can be described as

$$\varepsilon_q=\frac{u_j^*-u_i^*}{l}+\left(\frac{6y}{l^2}-\frac{12xy}{l^3}\right)v_i^*+\left(\frac{4y}{l}-\frac{6xy}{l^2}\right)\theta_i^*+\left(-\frac{6y}{l^2}+\frac{12xy}{l^3}\right)v_j^*+\left(\frac{2y}{l}-\frac{6xy}{l^2}\right)\theta_j^* \tag{5}$$

where $\left[u_i^*,v_i^*,\theta_i^*,u_j^*,v_j^*,\theta_j^*\right]^T$ stand for the *i*-th and *j*-th nodal displacement vectors of the *e*-th element; *l* means the length of element.

The DOFs of elemental nodal displacements $u_i^*,v_i^*,\theta_i^*,u_j^*,v_j^*,\theta_j^*$ is rewritten as *e*1, *e*2, *e*3, *e*4, *e*5, *e*6. The unit strain impulse response function $h_q^\varepsilon(t)$ at location *q* can be calculated by the unit displacement impulse response function with the similar expression of Eq. (5)

$$\begin{aligned} h_q^\varepsilon(t)=&\frac{h_{e4}(t)-h_{e1}(t)}{l}+\left(\frac{6y}{l^2}-\frac{12xy}{l^3}\right)h_{e2}(t)+\left(\frac{4y}{l}-\frac{6xy}{l^2}\right)h_{e3}(t) \\ &+\left(-\frac{6y}{l^2}+\frac{12xy}{l^3}\right)h_{e5}(t)+\left(\frac{2y}{l}-\frac{6xy}{l^2}\right)h_{e6}(t) \end{aligned} \tag{6}$$

where $h_{e1}(t),h_{e2}(t),h_{e3}(t),h_{e4}(t),h_{e5}(t),h_{e6}(t)$ are the unit displacement impulse response function for the DoFs *e*1, *e*2, *e*3, *e*4, *e*5, *e*6, respectively.

For a structural system with zero initial conditions, the displacement, strain and acceleration responses from the *m*-th, *q*-th, *s*-th DOFs at instant $t_n$ under general external excitation $f(t)$ can be expressed as Eqs. (7-9), respectively

$$u_m(t_n) = \int_0^{t_n} h_m(t_n - \tau) f(\tau) d\tau \tag{7}$$

$$\varepsilon_q(t_n) = \int_0^{t_n} h_q^{\varepsilon}(t_n - \tau) f(\tau) d\tau \tag{8}$$

$$\ddot{u}_s(t_n) = \int_0^{t_n} \ddot{h}_s(t_n - \tau) f(\tau) d\tau \tag{9}$$

where $u_m(t_n)$, $\varepsilon_q(t_n)$, $\ddot{u}_s(t_n)$ are the displacement, strain, acceleration measurements; $h_m(t_n - \tau)$, $h_q^{\varepsilon}(t_n - \tau)$, $\ddot{h}_s(t_n - \tau)$ denote the unit displacement, strain, acceleration impulse response functions, respectively.

The discrete form of Eqs. (7-9) can be expressed as following three equations, respectively

$$u_m(t_n) = \sum_{\tau=0}^{t_n} h_m(t_n - \tau) f(\tau) \tag{10}$$

$$\varepsilon_q(t_n) = \sum_{\tau=0}^{t_n} h_q^{\varepsilon}(t_n - \tau) f(\tau) \tag{11}$$

$$\ddot{u}_s(t_n) = \sum_{\tau=0}^{t_n} \ddot{h}_s(t_n - \tau) f(\tau) \tag{12}$$

The heterogeneous dynamic responses and input force can be expressed as

$$y_{u_m} = \left[u_m(t_0), u_m(t_1), ..., u_m(t_n)\right]^T \tag{13}$$

$$y_{\varepsilon_q} = \left[\varepsilon_q(t_0), \varepsilon_q(2), ..., \varepsilon_q(t_n)\right]^T \tag{14}$$

$$y_{\ddot{u}_s} = \left[\ddot{u}_s(t_0), \ddot{u}_s(t_1), ..., \ddot{u}_s(t_n)\right]^T \tag{15}$$

$$F = \left[f(t_0), f(t_1), ..., f(t_n)\right]^T \tag{16}$$

The relationship between the output responses and input force can be written as

$$Y_u = H_u F,\ Y_\varepsilon = H_\varepsilon F,\ Y_{\ddot{u}} = H_{\ddot{u}} F \tag{17}$$

where $Y_u$, $Y_\varepsilon$, $Y_{\ddot{u}}$ are the assembled displacement, strain and acceleration measurements, $Y_u = \left[y_{u_1}, y_{u_2}, ..., y_{u_n}\right]^T$, $Y_\varepsilon = \left[y_{\varepsilon_1}, y_{\varepsilon_2}, ..., y_{\varepsilon_n}\right]^T$, $Y_{\ddot{u}} = \left[y_{\ddot{u}_1}, y_{\ddot{u}_2}, ..., y_{\ddot{u}_n}\right]^T$. The dimensions of $Y_u$, $Y_\varepsilon$, $Y_{\ddot{u}}$ are $(u_n \times t_n) \times 1$, $(\varepsilon_n \times t_n) \times 1$, $(\ddot{u}_n \times t_n) \times 1$, and $u_n$, $\varepsilon_n$, $\ddot{u}_n$ represent the number of displacement sensors, strain gauges, accelerometers. The dimension of external excitation $F$ is $t_n \times 1$.

In Eq. (17), $H_u = [H_{u_1}, H_{u_2}, ..., H_{u_n}]^T$, $H_\varepsilon = \left[H_{\varepsilon_1}, H_{\varepsilon_2}, ..., H_{\varepsilon_n}\right]^T$, $H_{\ddot{u}} = \left[H_{\ddot{u}_1}, H_{\ddot{u}_2}, ..., H_{\ddot{u}_n}\right]^T$, the dimensions of $H_u$, $H_\varepsilon$, $H_{\ddot{u}}$ are $(u_n \times t_n) \times t_n$, $(\varepsilon_n \times t_n) \times t_n$, $(\ddot{u}_n \times t_n) \times t_n$, and they can be given by following equations, respectively

$$H_u = \begin{bmatrix} h_{u_n}(t_0) & 0 & 0 & 0 & 0 \\ h_{u_n}(t_1) & h_{u_n}(t_0) & 0 & 0 & 0 \\ h_{u_n}(t_2) & h_{u_n}(t_1) & h_{u_n}(t_0) & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_{u_n}(t_n) & h_{u_n}(t_{n-1}) & h_{u_n}(t_{n-2}) & \cdots & h_{u_n}(t_0) \end{bmatrix} \tag{18}$$

$$H_\varepsilon = \begin{bmatrix} h^\varepsilon_{\varepsilon_n}(t_0) & 0 & 0 & 0 & 0 \\ h^\varepsilon_{\varepsilon_n}(t_1) & h^\varepsilon_{\varepsilon_n}(t_0) & 0 & 0 & 0 \\ h^\varepsilon_{\varepsilon_n}(t_2) & h^\varepsilon_{\varepsilon_n}(t_1) & h^\varepsilon_{\varepsilon_n}(t_0) & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h^\varepsilon_{\varepsilon_n}(t_n) & h^\varepsilon_{\varepsilon_n}(t_{n-1}) & h^\varepsilon_{\varepsilon_n}(t_{n-2}) & \cdots & h^\varepsilon_{\varepsilon_n}(t_0) \end{bmatrix} \tag{19}$$

$$H_{\ddot{u}} = \begin{bmatrix} \ddot{h}_{\ddot{u}_n}(t_0) & 0 & 0 & 0 & 0 \\ \ddot{h}_{\ddot{u}_n}(t_1) & \ddot{h}_{\ddot{u}_n}(t_0) & 0 & 0 & 0 \\ \ddot{h}_{\ddot{u}_n}(t_2) & \ddot{h}_{\ddot{u}_n}(t_1) & \ddot{h}_{\ddot{u}_n}(t_0) & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \ddot{h}_{\ddot{u}_n}(t_n) & \ddot{h}_{\ddot{u}_n}(t_{n-1}) & \ddot{h}_{\ddot{u}_n}(t_{n-2}) & \cdots & \ddot{h}_{\ddot{u}_n}(t_0) \end{bmatrix} \tag{20}$$

It is noted that the magnitudes of heterogeneous measurements, such as displacement, strain and acceleration are very different, so rescaling coefficients are introduced into Eq. (17) as follows

$$\begin{aligned} \tilde{Y}_u &= a_u Y_u = a_u H_u F = \tilde{H}_u F \\ \tilde{Y}_\varepsilon &= a_\varepsilon Y_\varepsilon = a_\varepsilon H_\varepsilon F = \tilde{H}_\varepsilon F \\ \tilde{Y}_{\ddot{u}} &= a_{\ddot{u}} Y_{\ddot{u}} = a_{\ddot{u}} H_{\ddot{u}} F = \tilde{H}_{\ddot{u}} F \end{aligned} \tag{21}$$

where $a_u$, $a_\varepsilon$, $a_{\ddot{u}}$ are the rescaling coefficients, and they can be calculated by

$$a_u = \left\|Y_u\right\|_2^{-1},\ a_\varepsilon = \left\|Y_\varepsilon\right\|_2^{-1},\ a_{\ddot{u}} = \left\|Y_{\ddot{u}}\right\|_2^{-1} \tag{22}$$

where $\|\ \|_2$ represents the $L_2$ norm of the given vector.

The heterogeneous data fusion can be achieved by

$$Y = HF \tag{23}$$

where $Y = \left[\tilde{Y}_u, \tilde{Y}_\varepsilon, \tilde{Y}_{\ddot{u}}\right]^T$, $H = \left[\tilde{H}_u, \tilde{H}_\varepsilon, \tilde{H}_{\ddot{u}}\right]^T$, $\tilde{H}_u = a_u H_u, \tilde{H}_\varepsilon = a_\varepsilon H_\varepsilon, \tilde{H}_{\ddot{u}} = a_{\ddot{u}} H_{\ddot{u}}$.

In previous studies, response reconstruction technique has been applied into output-only structural identification with only one type of sensor. In practice, a multi-sensors monitoring system is usually installed on the large infrastructure, thus heterogeneous measurements, displacements, strains, accelerations, etc., are available. Herein, response reconstruction with multiple types of vibration data in time domain is derived. First, heterogeneous responses can be divided into two set, i.e., measurement set 1 $Y_{mea}^{set1}$ and set 2 $Y_{mea}^{set2}$, given by

$$\begin{cases} Y_{mea}^{set1} = H_1 F \\ Y_{mea}^{set2} = H_2 F \end{cases} \tag{24}$$

It is noted that there is no specific rule about how to divide the multi-type responses into two sets, but the number of sensors in the measurement set 1 should exceed the number of unknown external excitations on the structure.

Then, the unknown input force and dynamic responses of the second set can be calculated using the first set of measurements as follows

$$F = \left(H_1\right)^+ Y_{mea}^{set1} \tag{25}$$

$$Y_{rec}^{set2} = H_2\left(H_1\right)^+ Y_{mea}^{set1} \tag{26}$$

where $()^+$ means the pseudoinverse and transformation matrix $T_{12} = H_2\left(H_1\right)^+$.

For Eqs. (25) and (26), the ordinary least squares may lead to unbounded solution especially taking the noise-polluted measurements into consideration. In order to deal with the drifted estimation of external excitation and responses, Tikhonov regularization method is employed

$$F = \left(H_1^T H_1 + \lambda I\right)^{-1} H_1^T Y_{mea}^{set1} \tag{27}$$

$$Y_{rec}^{set2} = T_{12} Y_{mea}^{set1} = H_2\left(H_1^T H_1 + \lambda I\right)^{-1} H_1^T Y_{mea}^{set1} \tag{28}$$

where $\lambda$ stands for the non-negative regularization parameter; $I$ means the identity matrix.

As is known, the key point of using Tikhonov regularization technique lies in how to efficiently find the optimal regularization parameter $\lambda$. The *L*-curve method, the generalized cross-validation (GCV) method and the *S*-curve method have been adopted but suffer from comparatively expensive computation issue for a large-scale matrix. In addition, it may find that the *L*-curve doesn't have a distinct corner, leading to the difficulty in determining the regularization parameter. In recent years, Bayesian inference method has been developed to adaptively determine the regularization parameter, adopted in this study.

## 2.2 Bayesian inference method

In this section, a statistical Bayesian learning scheme is used to reconstruct the unknown input force. The unknown force *F* is modeled in the posterior probability density function (PDF) $p\left(F,\sigma^2,\tau^2 \middle| Y\right)$ through hierarchical modeling as follows

$$p\left(F,\sigma^2,\tau^2 \middle| Y\right) \propto p\left(Y \middle| F,\sigma^2\right) p\left(F \middle| \tau^2\right) p\left(\sigma^2\right) p\left(\tau^2\right) \tag{29}$$

where $p\left(Y \middle| F,\sigma^2\right)$ means the likelihood function and $p\left(F \middle| \tau^2\right)$ represents the prior PDF, and they can be expressed as

$$p\left(Y \middle| F,\sigma^2\right) \propto \frac{1}{\sigma^{n_0 N}} \exp\left(-\frac{1}{2\sigma^2}\left\|HF - Y\right\|^2\right) \tag{30}$$

$$p\left(F \middle| \tau^2\right) \propto \frac{1}{\tau^{n_f N}} \exp\left(-\frac{1}{2\tau^2}\left\|F\right\|^2\right) \tag{31}$$

where $n_0$ means the total number of measurements including displacements, strains and accelerations, i.e., $n_0 = u_n + \varepsilon_n + \ddot{u}_n$; $\sigma$ and $\tau$ stand for the standard deviation and scaling parameter; $n_f$ represents the number of force.

For the hyperparameters $\sigma^2$ and $\tau^2$, $p\left(\sigma^2\right)$ and $p\left(\tau^2\right)$ are their conjugate prior PDFs, modeled as the following inverse Gamma distribution

$$p\left(\sigma^2\right)=\frac{b_1^{a_1}}{\Gamma\left(a_1\right)}\sigma^{-2\left(a_1+1\right)}e^{-b_1\sigma^{-2}} \tag{32}$$

$$p\left(\tau^2\right)=\frac{b_2^{a_2}}{\Gamma\left(a_2\right)}\tau^{-2\left(a_2+1\right)}e^{-b_2\tau^{-2}} \tag{33}$$

where $a_1, b_1, a_2, b_2$ denote the non-negative hyperparameters.

Combining Eqs. (30-33) with Eq. (29), the posterior PDF is written as

$$p\left(F,\sigma^2,\tau^2 \left|Y\right.\right)\propto\frac{\tau^{-2\left(a_2+1\right)-n_f N}}{\sigma^{2\left(a_1+1\right)+n_0 N}}\exp\left(-\frac{1}{2\sigma^2}\left\|HF-Y\right\|^2-\frac{1}{2\tau^2}\left\|F\right\|^2-b_1\sigma^{-2}-b_2\tau^{-2}\right) \tag{34}$$

The maximum a posteriori estimation is determined by

$$\left\{\hat{F},\hat{\sigma}^2,\hat{\tau}^2\right\}=\arg\max_{\left\{F,\sigma^2,\tau^2\right\}}\left\{p\left(F,\sigma^2,\tau^2\left|Y\right.\right)\right\} \tag{35}$$

By the logarithm and the negative of Eq. (34), the following equation is obtained

$$\begin{aligned}J\left(F,\sigma^2,\tau^2\right)=&\frac{1}{2\sigma^2}\left\|HF-Y\right\|^2+\frac{1}{2\tau^2}\left\|F\right\|^2+b_1\sigma^{-2}+b_2\tau^{-2}\\&+\left[2\left(a_2+1\right)+n_f N\right]\ln\tau+\left[2\left(a_1+1\right)+n_0 N\right]\ln\sigma\end{aligned} \tag{36}$$

Setting the partial derivative of $J\left(F,\sigma^2,\tau^2\right)$ to zero yields

$$\frac{\partial J\left(F,\sigma^2,\tau^2\right)}{\partial F}=0,\frac{\partial J\left(F,\sigma^2,\tau^2\right)}{\partial\sigma^2}=0,\frac{\partial J\left(F,\sigma^2,\tau^2\right)}{\partial\tau^2}=0 \tag{37}$$

The optimal solutions $\left\{\hat{F},\hat{\sigma}^2,\hat{\tau}^2\right\}$ can be obtained by following equations, respectively

$$\hat{F}=\left(H^T H+\frac{\hat{\sigma}^2}{\hat{\tau}^2}I\right)^{-1}H^T Y \tag{38}$$

$$\hat{\sigma}^2=\frac{\left\|H\hat{F}-Y\right\|^2+2b_1}{2\left(a_1+1\right)+n_0 N} \tag{39}$$

$$\hat{\tau}^2=\frac{\left\|\hat{F}\right\|^2+2b_2}{2\left(a_2+1\right)+n_f N} \tag{40}$$

The regularization parameter can be automatically determined by $\lambda=\frac{\hat{\sigma}^2}{\hat{\tau}^2}$. Then, the unmeasured input force is reconstructed.

## 3 Q-LEARNING HYBRID EVOLUTIONARY ALGORITHM

A Q-learning hybrid evolutionary algorithm (QHEA) is proposed by integrating Jaya algorithm, DE, Q-learning algorithm. When solving structural damage identification problem using the proposed QHEA, some analogies with Q-learning framework should be given. The individuals in the population are the candidate stiffness vectors to be identified, which are viewed as the learning agents; the environment is regarded as the search domain of these candidate stiffness vectors; the states refer to the possible operations from strategy pool, i.e., DE/rand/1, DE/rand/2, DE/current-to-best/1 and Jaya mutation for candidate solutions; the action implies it switches from one updating strategy to another.

In each iteration, the proposed QHEA can enable individuals adaptively and continuously select the most suitable search operation from the strategy pool under the guidance of the Q-learning based on the maximum Q-value in the Q-table. The structure of the proposed QHEA is shown in Figure 1. It is clear that the proposed QHEA has a simple algorithmic structure and it is easy to operate.

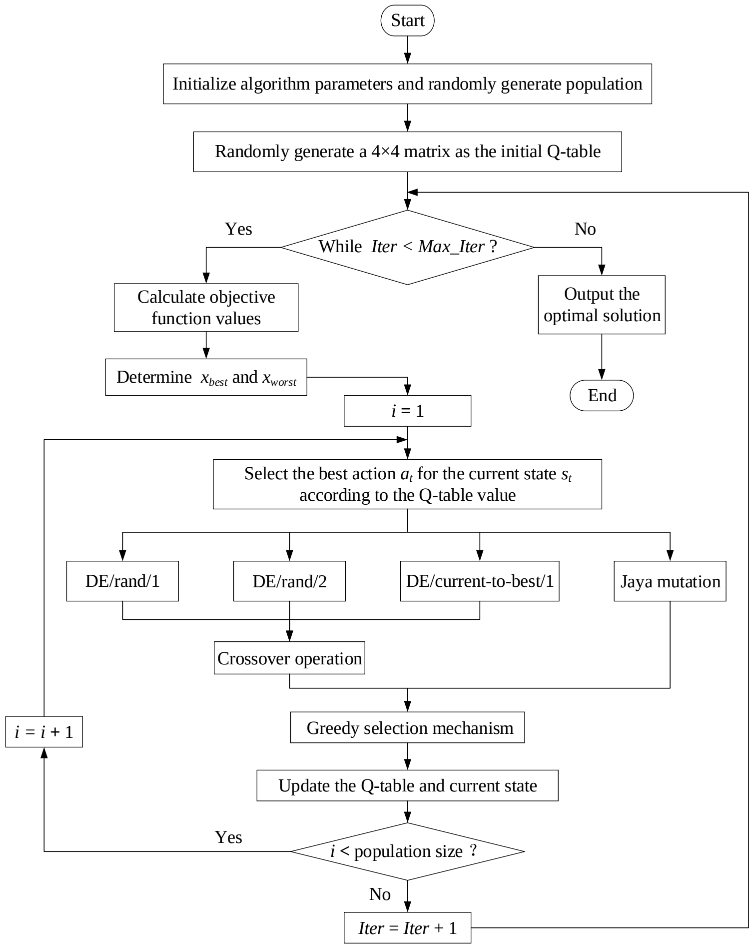


**Figure 1**: The structure of the proposed QHEA

## 4 IMPLEMENTATION PROCEDURES

In the optimization-based damage identification problem, the purpose is to find the best structural parameters $\theta$ by minimizing the discrepancy between the measured responses $Y_{mea}^{set2}$ and the reconstructed responses $Y_{rec}^{set2}(\theta)$ of the second set from the damaged structure as follows

$$obj = \left\| Y_{mea}^{set2} - Y_{rec}^{set2}(\theta) \right\|_2 \tag{41}$$

where $obj$ represents the objective function to be optimized; The unknown structural parameter is calculated by $\theta_i = 1 - \alpha_i$ within the range of [0, 1].

In this section, an iterative strategy is developed to identify the unknown structural damages with the incomplete output-only responses, and its flowchart is shown in Figure 2. The measured multiple types of dynamic responses including displacements, strains, accelerations, are divided into two different measurement sets, i.e., measurement set 1 $Y_{mea}^{set1}$ and measurement set 2 $Y_{mea}^{set2}$. As presented in Figure 2, measurement set 1 is utilized to reconstruct unmeasured input force based on Bayesian inference regularization method while measurement set 2 is employed to construct the objective function to be optimized by the proposed QHEA. The structural damages and the unknown external excitation can be iteratively estimated by minimizing the objective function defined in Eq. (41) until the termination criterion is satisfied.

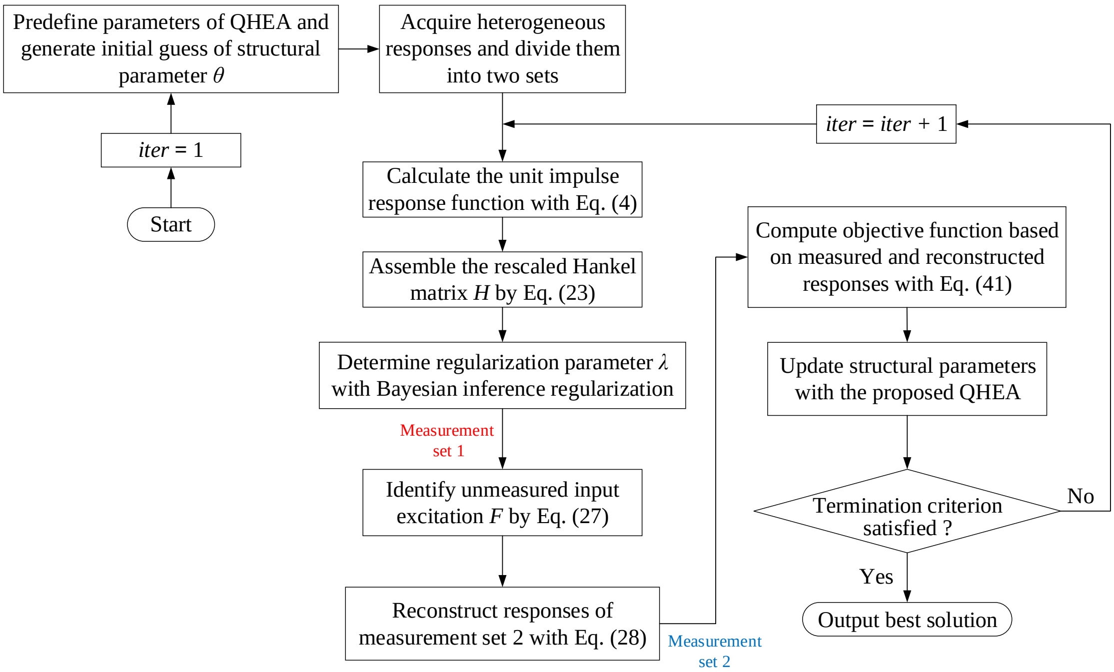


**Figure 2**: Implementation procedures of proposed identification method

## 5 EXPERIMENTAL STUDIES

### 5.1 Description of structural model

Experimental studies on a five-floor steel frame model in the laboratory are carried out to further validate the effectiveness of the proposed output-only strategy for structural damage identification. Figure 3 depicts the experimental setup and geometric dimensions of laboratory model. The height, length and width of the frame structure are 1750 mm, 300 mm and 400 mm, respectively. In each floor, the dimensions of story slab are 300 × 400 × 15 mm and there are four identical columns with the cross-section of 40 mm × 4 mm. The finite element model of the steel frame can be simplified as a 5-DOF shear-type system in consideration of the comparatively strong floors and weak columns. The mass density and initial elastic modulus of steel material are 7850 kg/m$^3$ and 2.06 × 10$^{11}$ N/m$^2$, respectively. A vibration exciter (Modal Shop 2100E11) is anchored on counterforce wall to provide sinewave input excitation at the top floor of frame structure. A power amplifier is employed to generate sufficient power to actuate the vibration exciter. In order to directly measure external input excitation, a force sensor (PCB208C02) is installed between the shaker and the frame model.

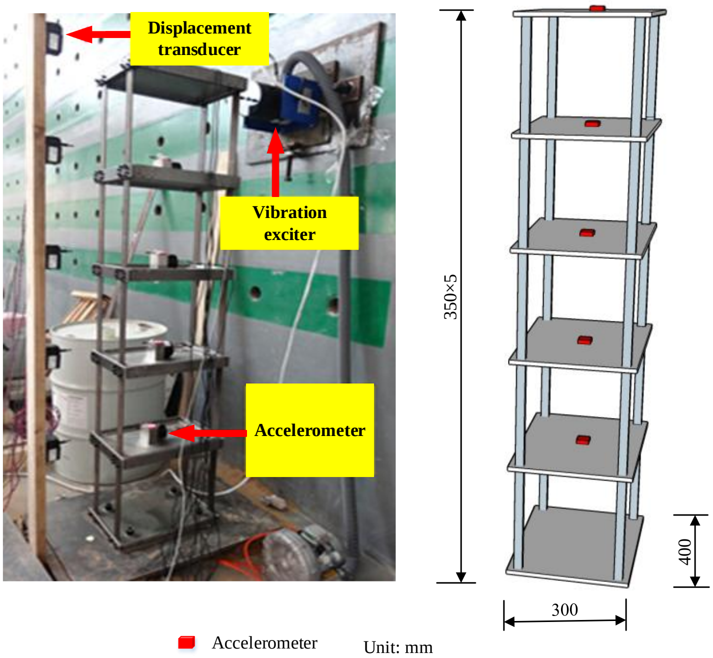


**Figure 3**: The experimental setup of five-floor steel frame structure.

## 5.2 Identification of two damages scenarios

In order to test the performance of the proposed method in detecting, localizing, and quantifying structural damages, artificial damages are introduced into the steel frame structure by reducing the cross-section of columns. Two damage scenarios are considered, and four tests are implemented in each damage scenario. All columns in the fifth floor are replaced from original width of 40 mm to a smaller width of 36 mm, denoted as scenario 1, which results in 10% stiffness reduction for element 5. In the same way, all columns in the fourth floor are replaced from original 40 mm to more thinner 32 mm, named as scenario 2, which leads to 20% equivalent stiffness reduction for element 4. Herein, mass alteration can be directly neglected owing to less than 2% slight reductions of mass in these two damage scenarios, rendering it hard to be successfully detected.

The measurement set 1 is used to reconstruct the responses of the measurement set 2. Structural damages are identified by minimizing the difference between the measured and reconstructed responses in the second set. The proposed QHEA is utilized as the search tool. Figure 4 provides the mean values of identified damage results for scenario 1 and scenario 2.

In scenario 1, the identified damage extent in the fifth floor is 11.94%. For scenario 3, the identified damage extent in the fourth floor is 22.43%. Both damage locations and severities can be well identified. In addition. Figure 5 presents the convergence process of the identified damage extents. It is clearly observed that after around 40 iterations, the identified mean values converge to the neighborhood of the actual damage extents. More reliable identification results are obtained if more tests are available. The experimental study demonstrates the proposed method can be successfully applied into output-only structural damage identification.

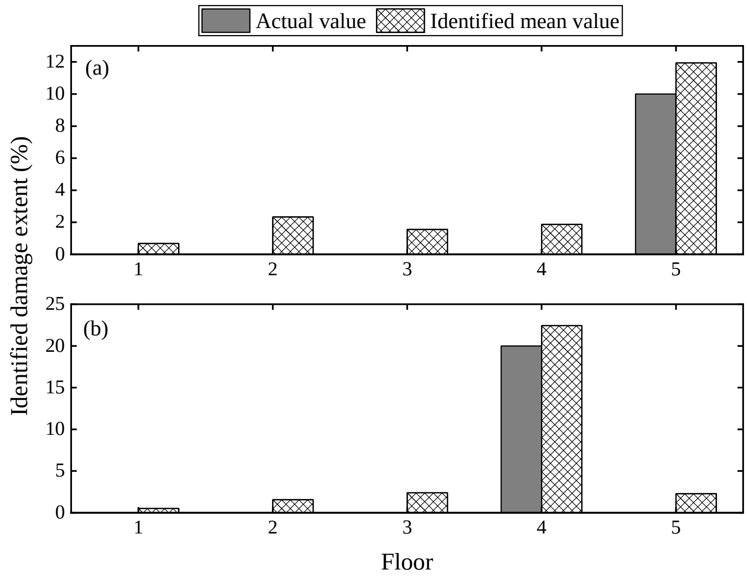


**Figure 4**: Identified damage results with proposed output-only method: (a) scenario 1; (b) scenario 2.

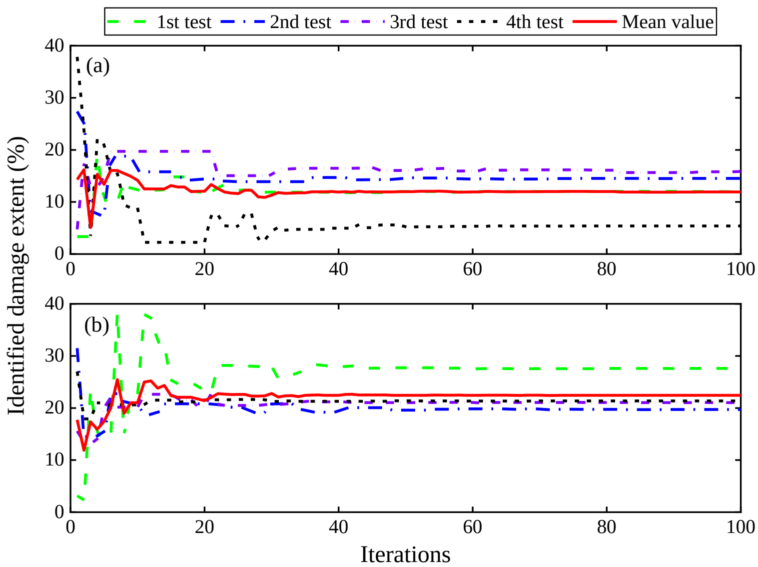


**Figure 5**: The convergence process of the identified damage extents: (a) scenario 1; (b) scenario 2.

## 6 CONCLUSIONS

- A novel output-only structural damage identification approach based on Q-learning hybrid evolutionary algorithm and Bayesian inference regularization with heterogeneous data fusion is proposed. Multi-type responses including displacement, strain and acceleration time histories are fused and rescaled for response reconstruction.
- More reliable identification results are obtained if more tests are available. The experimental study on a five-floor steel frame structure demonstrates the proposed method can be successfully applied into output-only structural damage identification.


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