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Experimental Verification of Parameter Identification Method based on Symbolic Time Series Analysis and Adaptive Immune Clonal Selection Algorithm

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ABSTRACT

The parameter identification method based on symbolic time series analysis (STSA) and adaptive immune clonal selection algorithm (AICSA) was experimentally verified using a 5-story experimental model structure. In the experimental verification, both single and multiple damage scenarios were studied. A 5-story structure was initially healthy with all original columns intact. The single-damage case, the double-damage or the triple-damage case was simulated by replacing the columns of one, two or three different floors, respectively. The experimental results have shown that the parameter identification method based on STSA and AICSA can successfully identify structure parameters only utilizing measured acceleration information for various damage scenarios under different excitation conditions. The proposed approach was shown promising for application of SHM on buildings.

Keywords: structural health monitoring; clonal selection algorithm; symbolic time series analysis; adaptive immune; building structures;

1 INTRODUCTION

A new parameter identification method based on symbolic time series analysis (STSA) and adaptive immune clonal selection algorithm (AICSA) was proposed in reference [1]~[4]. To better assess the performance of the proposed methodology, experimental validation of the proposed approach has been conducted. Following the detailed description of the experimental setups, experimental results are provided which show the proposed approach to be very promising. A 5-story structure was initially healthy with all original columns intact. Two columns of one floor were then replaced by weak columns (of the same material and integrity as healthy columns, but with smaller cross-sectional area) to simulate a single-damage case. The double-damage or triple-damage case was simulated by replacing the columns of two or three different stories, respectively. Under the basement of the structure, there were some bearings so that

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the structure could have a ground motion. The experimental results have shown that the proposed approach can successfully identify parameters of structure utilizing measured acceleration information for various damage scenarios under different excitation conditions. The proposed approach was shown promising for application of SHM on buildings.

2 PROPOSED METHOD

2.1 Procedure

In the research field of structural parameter identification, the time response of the system is usually compared with that of a parameterized model using a norm or some performance criterion to give us a measure of how well the model explains the system.

We will explain our methodology using a physical system with input u and output y. Let $y(t_i)$ $(i = 1, \dots, T)$ denote the value of the actual system at the ith discrete time step. Suppose that a parameterized model able to capture the behavior of the physical system is developed and this model depends on a set of n parameters, i.e., $x = (x_1, x_2, \dots, x_n)^T \in R^n$. Given a candidate parameter value x and a guess $\hat{X}_0$ of the initial state, $\hat{y}(t_i)$ $(i = 1, \dots, T)$, the value of the parameterized model, i.e., the identified system at the ith discrete time step, can be obtained. Hence, the problem of system identification boils down to finding a set of parameters that minimize the prediction error between the system output $y(t_i)$, which is the measured data, and the model output $\hat{y}(x, t_i)$, which is calculated at each time instant t_i .

Usually, our interest lies in minimizing the predefined error norm of the time series outputs, e.g., the following mean square error (MSE) function,

$$f(x) = \frac{1}{T} \sum_{i=1}^{T} \| y(t_i) - \hat{y}(x, t_i) \|^2 \tag{1}$$

where $\|\cdot\|$ represents the Euclidean norm of vectors. Formally, the optimization problem requires one to find a set of n parameters $x^* \in R^n$ so that a certain quality criterion is satisfied, namely, that the error norm $f(\bullet)$ is minimized. The function $f(\bullet)$ is called a fitness function or objective function. Typically, an objective function that reflects the goodness of the solution is chosen.

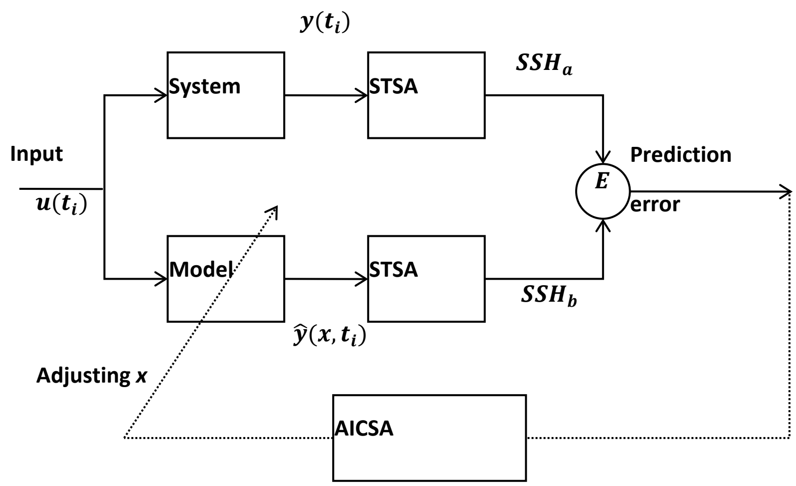

Figure 1. Procedure of AICSA combining STSA for identification of structural parameters.

In our methodology, we introduce an index, the relative state sequence histogram error (RSSHe), to measure the distance between SSH_a and SSH_b (SSH_a and SSH_b are the system output and model output, respectively). The definition is:

$$\begin{cases} SSH_a = \left[d_a^0, d_a^1, \ldots, d_a^{Q-1}\right] \\ SSH_b = \left[d_b^0, d_b^1, \ldots, d_b^{Q-1}\right] \end{cases}, \quad Q = 2^r \quad \text{and} \quad RSSHe = \sqrt{\frac{\sum_{i=0}^{i=Q-1}(d_b^i - d_a^i)^2}{\sum_{i=0}^{i=Q-1}(d_a^i)^2}} \tag{2}$$

where $d_{a/b}^i$ is the frequency of state i in SSH_a or SSH_b. The procedure of AICSA combining STSA for identification of structural parameters was shown in Figure 1.

2.2 Guideline for parameter selection

In STSA, the main parameters are the word length and window length, and they control the resolution of the whole representation space. For a window length T and word length r, two limiting cases of SSH are predefined as:

- Case 1: All states in the SSH are distributed uniformly, and the frequency of each state is $\frac{1}{2^r}$.
- Case 2: Only one state in the SSH has the frequency of 1; the frequencies of the other states are 0.

Suppose there are two different $SSHs$: SSH_a and SSH_b. From Equation (3), when SSH_a corresponds to limiting case 1 and SSH_b to limiting case 2, the maximum value of $RSSHe$ is:

$$RSSHe_{max} = \sqrt{\frac{\sum_{i=0}^{i=Q-1}\left(d_b^i - d_a^i\right)^2}{\sum_{i=0}^{i=Q-1}\left(d_a^i\right)^2}} = \sqrt{\frac{(1-\frac{1}{2^r})^2 + \left(\frac{1}{2^r}\right)^2(2^r-1)}{(\frac{1}{2^r})^2 * 2^r}} = \sqrt{2^r - 1} \tag{3}$$

When SSH_a and SSH_b are the same, the minimum $RSSHe$ is 0. Then,

$$RSSHe \in [RSSHe_{min}, RSSHe_{max}] = [0, \sqrt{2^r - 1}] \tag{4}$$

Since the minimum changeable unit in SSH is $\frac{1}{T-r+1}$, the change in frequency of one state in SSH will absolutely be related to the change in frequencies of other states. Supposing that there are only two minimum unit differences between SSH_a and SSH_b, the minimum distinguishable $RSSHe$ is:

$$RSSHe_{dis} = \sqrt{\frac{\sum_{i=0}^{i=Q-1}(d_b^i - d_a^i)^2}{\sum_{i=0}^{i=Q-1}(d_a^i)^2}} = \sqrt{\frac{(\frac{1}{T-r+1})^2 + (\frac{1}{T-r+1})^2}{\sum_{i=0}^{i=Q-1}(d_a^i)^2}} = \frac{\sqrt{\frac{2}{\sum_{i=0}^{i=Q-1}(d_a^i)^2}}}{T-r+1} \quad (5)$$

When SSH_a is limiting case 1, the maximum distinguishable $RSSHe_{dis}^{max}$ will be:

$$RSSHe_{dis}^{max} = \frac{\sqrt{2^{(r+1)}}}{T-r+1} \quad (6)$$

When SSH_a is limiting case 2, the minimum distinguishable $RSSHe_{dis}^{min}$ will be:

$$RSSHe_{dis}^{min} = \frac{\sqrt{2}}{T-r+1} \quad (7)$$

The resolution is:

$$[RSSHe_{dis}^{min}, RSSHe_{dis}^{max}] = [\frac{\sqrt{2}}{T-r+1}, \frac{\sqrt{2^{(r+1)}}}{T-r+1}] \quad (8)$$

Note that we also need to consider the number of the possible distributions of states in one SSH. If the number of states in SSH is 2^r and the minimum changeable unit is $\frac{1}{T-r+1}$, finding the total number of possible distributions N_{SSH} of SSH boils down to a classic combination problem, which is 'put $T-r+1$ identical balls in 2^r different boxes. The combinatorial number is:

$$N_{SSH} = C_{T-r+2^r}^{2^r-1} \quad (9)$$

As we can see, longer window and word lengths are related to higher resolution, which means that the self and non-self-spaces can be separated much more accurately. This is the key to obtaining accurate structural parameter identification.

So far, our discussion of the effect of the window length and word length has been based on a case in which only one story's output (raw acceleration data) is used, but structures with multiple degrees of freedom (MDOF) may have more outputs than that. Supposing the outputs from N stories can be obtained, the boundary of the solution space is:

$$RSSHe \in [RSSHe_{min}, RSSHe_{max}]^N = [0, \sqrt{2^r - 1}]^N \quad (10)$$

The resolution falls to:

$$[RSSHe_{dis}^{min}, RSSHe_{dis}^{max}]^N = [\frac{\sqrt{2}}{T-r+1}, \frac{\sqrt{2^{(r+1)}}}{T-r+1}]^N \quad (11)$$

Also, the total number of possible distributions increases to:

$$[N_{SSH}]^N = [C_{T-r+2^r}^{2^r-1}]^N \tag{12}$$

From Equations (10) to (12), it is evident that as more story outputs are obtained, the more accurate the identification results will be.

The root-mean-square error (RMSe) was used to verify the feasibility and performance of the identification results. RMSe is defined as

$$RMSe = \sqrt{\frac{\sum_{i=1}^{n}(k_{c,i}-k_{real,i})^2}{\sum_{i=1}^{n} k_{real,i}^2}} \tag{13}$$

where $k_{c,i}$ and $k_{real,i}$ are the candidate stiffness and real stiffness of the ith story, respectively.

3 EXPERIMENTAL SETUP

A series of experiments were performed to verify the performance of our proposed approach. The model structure is depicted in Figure 2.

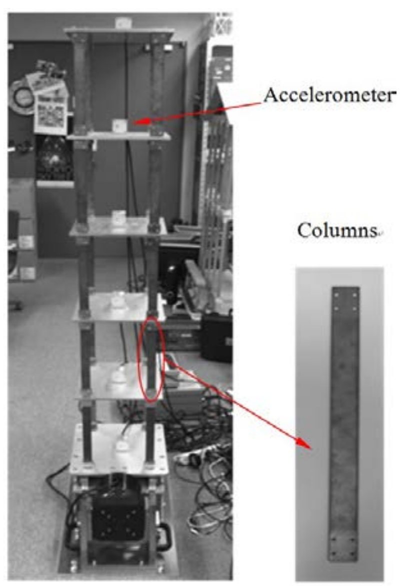

Figure 2. Experimental setup of small model

This experimental setup imitates a 5-story shear frame buildings. The story mass is decided by the aluminum floor slab which is 2.43 kg for each floor. The story stiffness is decided by the bronze plate spring with the size of 0.0025m×0.030m×0.24 m. The Young's modulus of bronze is 1.00×10^{11} N/m^2, so the interfloor stiffness is 1.36×10^4 N/m. The structure was initially healthy with all original columns intact, and the natural frequency of the first to the fifth mode is 3.39Hz ,9.89Hz, 15.59Hz, 20.03 Hz and 22.84 Hz, respectively.

The damage was introduced by replacing columns by weak columns with the size of 0.0030m×0.0060m×0.24 m, shown in Figure 3. By replacing two columns in a story, the story stiffness was reduced by 33%.

Figure 3. Healthy (Left) and Damaged (Right) Columns

Under the basement of the structure, there were some bearings so that the structure could have a ground motion. The force input to the structure is provided with an electrodynamic shaker as shown in Figure 4. One acceleration sensor was installed on the basement to measure the ground motion. The sensor installed on each floor plate was used to measure the acceleration response of each floor.

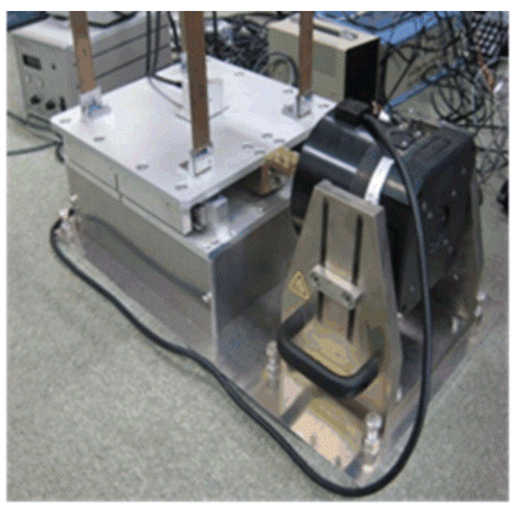

Figure 4. Bearings and Shaker

4 PROCEDURE

The 5-story structure was initially healthy with all original columns intact. The force input to the structure was provided by the shaker to obtain the acceleration data of the 5th story of the structure in normal state. Then, two columns of the first story were then replaced by weaker columns (of the same material and integrity as healthy columns but with a smaller cross-sectional area) to simulate the abnormal state of the structure as stiffness reduction at a single story. The abnormal state of stiffness reduction at two stories was simulated by replacing two columns of the 1st story as well as those of the 3rd story. Finally, two columns of the 5th floor were also replaced to simulate the abnormal state case of stiffness reduction at three stories.

For only small completely vibration of the experimental setup is needed, and also considering avoiding the resonance region, a 1.1-Hz sine wave was used as the input signal in the experiments. Part of the input signal (0 to 20 s) is shown in Figure 5. The response of the experiential structure was recorded for 30s at a sampling frequency of 100 Hz; the total data length was 3000.

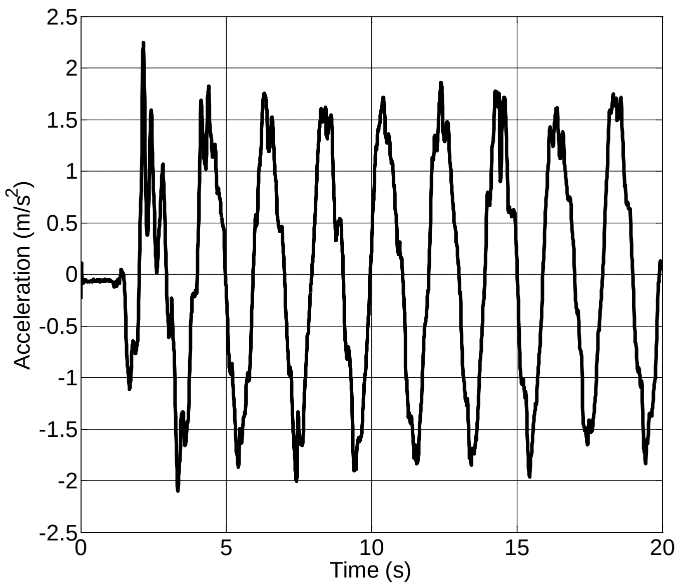

Figure 5. One typical acceleration signal

5 DAMAGE IDENTIFICATION RESULTS

The results summarized in Tables 1~4 show that RMSe is acceptable with our proposed method. In the verification, every case is calculated 10 times independently and average RMSe can be obtained. The average RMSe for each case is 3.64%, 3.63%, 3.82%and 3.88%, respectively. The trend is same as that of numerical simulation.

Table 1. Results of experimental verification of original structure. (Unit is 10 kN/m)

	True stiffness	Process number									
		1	2	3	4	5	6	7	8	9	10
k1	1.36	1.34	1.36	1.38	1.40	1.39	1.35	1.35	1.34	1.33	1.33
k2	1.36	1.37	1.40	1.34	1.36	1.34	1.34	1.39	1.38	1.32	1.37
k3	1.36	1.37	1.35	1.36	1.33	1.39	1.34	1.37	1.38	1.36	1.36
k4	1.36	1.33	1.37	1.38	1.33	1.34	1.37	1.36	1.35	1.38	1.32
k5	1.36	1.33	1.34	1.39	1.34	1.40	1.36	1.39	1.37	1.40	1.35
RMSe (%)	0.00	3.63	3.40	3.37	4.35	4.35	2.62	3.37	2.65	4.82	3.83

Table 2. Results of experimental verification of single-damage case. (Unit is 10 kN/m)

	True stiffness	Process number									
		1	2	3	4	5	6	7	8	9	10
k1	0.91	0.92	0.90	0.92	0.92	0.90	0.89	0.90	0.90	0.91	0.91
k2	1.36	1.35	1.35	1.38	1.36	1.35	1.39	1.35	1.34	1.39	1.36
k3	1.36	1.38	1.37	1.36	1.36	1.38	1.36	1.36	1.34	1.36	1.33
k4	1.36	1.34	1.38	1.36	1.38	1.36	1.37	1.34	1.34	1.34	1.34
k5	1.36	1.37	1.33	1.36	1.38	1.35	1.37	1.38	1.36	1.39	1.35
RMSe (%)	0.00	3.63	4.17	2.21	3.40	3.08	3.60	3.73	3.92	5.01	3.52

Table 3. Results of experimental verification of double-damage case. (Unit is 10 kN/m)

	True stiffness	Process number									
		1	2	3	4	5	6	7	8	9	10
k1	0.91	0.91	0.93	0.92	0.89	0.89	0.91	0.92	0.93	0.93	0.90
k2	1.36	1.33	1.35	1.34	1.34	1.35	1.35	1.36	1.38	1.39	1.38
k3	0.91	0.91	0.90	0.90	0.90	0.92	0.91	0.90	0.91	0.90	0.89
k4	1.36	1.36	1.38	1.34	1.37	1.37	1.34	1.35	1.35	1.37	1.38
k5	1.36	1.38	1.36	1.33	1.35	1.36	1.34	1.38	1.34	1.36	1.39
RMSe (%)	0.00	4.07	3.45	4.92	3.63	2.62	3.16	2.96	3.80	4.25	5.39

Table 4. Results of experimental verification of triple-damage case. (Unit is 10 kN/m)

	True stiffness	Process number									
		1	2	3	4	5	6	7	8	9	10
k1	0.91	0.92	0.91	0.93	0.90	0.90	0.89	0.94	0.92	0.91	0.92
k2	1.36	1.33	1.35	1.38	1.34	1.38	1.37	1.37	1.34	1.37	1.38
k3	0.91	0.91	0.92	0.91	0.92	0.91	0.93	0.90	0.90	0.90	0.90
k4	1.36	1.35	1.36	1.34	1.34	1.35	1.35	1.39	1.37	1.35	1.34
k5	0.91	0.90	0.91	0.90	0.93	0.92	0.93	0.94	0.95	0.89	0.88
RMSe (%)	0.00	3.88	1.54	3.95	4.02	2.95	4.00	5.75	4.70	3.35	4.68

6 CONCLUSION

In this paper, the parameter identification method based on STSA and AICSA was experimentally verified using a 5-story experimental model. The 5-story structure was initially healthy with all original columns intact. Two columns of one floor were then replaced by weak columns to simulate a single-damage case. The double-damage or triple-damage case was simulated by replacing the columns of two or three different floors, respectively. Under the basement of the structure, there were some bearings so that the structure could have a ground motion. The experimental results have shown that the proposed approach can successfully identify parameters of structure utilizing measured acceleration information for various damage scenarios under different excitation conditions. The proposed approach was shown promising for application of SHM on buildings.

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