Near Real-time Parametric Identification for a 2-D Engineering Truss with Vibration Macro-Strain

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ABSTRACT:

The increasing use of advanced sensing technologies such as optic fiber Bragg grating and embedded piezoelectric sensors for health monitoring of existing infrastructures necessitates the development of structural parametric identification methodologies using vibration induced strain histories. In this study, a three-step neural networks based strategy, called direct soft parametric identification (DSPI), is presented to identify structural member stiffness and damping parameters directly from free vibration-induced strain time series measurements. The rationality of the strain based DSPI methodology is explained and the theory basis for the construction of strain-based emulator neural network (SENN) and parametric evaluation neural network (PENN) are described according to the discrete time solution of the state space equation of structural free vibration. The performance of the proposed strategy are examined using an engineering truss structure model with a known mass distribution.

INTRODUCTION

Due to aging, misuse, lacking proper mainte-nance, and, in some cases, overstressing as a result of increasing load demands and changing envi-ronments, many of civil infrastructures are now deteriorating. Structural health monitoring (SHM) with the ability to continuingly report performance of a civil infrastructure is an emerging technology that could play an essential role in realizing a sustainable society.

The main research interests are the advanced sensing technologies and inverse analysis for structural parameters identification and damage detection.The most widely used global identification methodology is based on dynamic vibration measurements[1,2]. On one hand, from long-term vibration measurements under unknown/assumed stationary zero-mean Gaussian white noise ambient excitation, structural free vibration responses can be extracted using the Random Decrement (RD) technique by averaging time segments of the measurements. The implementation of a RD technique is simple and the estimation time for structural properties is short[3]. Therefore, developing a

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free vibration-based identification strategy is critical for long-term monitoring of civil infrastructures. On the other hand, to make fiber Bragg grating (FBG) sensor that is one of the widely used opticfiber sensing techniques less susceptible to local damages such as cracks that widely exist in civil infrastructures, the gauge length of a FBG sensor can be extended from several millimeters to centimeters or even meters for macro-strain measurements[4, 5]. The rapid development of strain sensing techniques necessitates the development of a new identification methodology based on strain measurements.

Neural networks have recently drawn considerable attention in civil engineering community due mainly to their ability to approximate an arbitrary continuous function and mapping. Indeed, modeling a linear or nonlinear structural system with neural networks has been increasingly recognized as one of the system identification paradigms[6-8]. Although several neural-network-based strategies are available for qualitative evaluation of damages that may have taken place in a structure[9, 10], it was not until recently that a quantitative way of detecting damage with neural networks has been proposed[11]. Unlike any conventional system identification technique that involves the inverse analysis with an optimization process, the strategies using dynamic responses can give the identification results in a substantially faster way and thus provide a viable tool for the on-line identification for a near real-time monitoring system[12-14].

This study is aimed at the development of a strain-based identification strategy, namely direct soft parametric identification (DSPI), for the monitoring of an engineering truss structure model. The performance of the three-step DSPI methodology are evaluated with a truss structure with a known mass distribution.

2. NOVEL DSPI STRATEGY BASED ON STRAIN MEASUREMENTS

2.1 General Methodology

Consider an N DOF viscously damped linear structural system. Under an initial displacement and a zero velocity, the free vibration of the structure can be described by,

$$M\ddot{x}+C\dot{x}+Kx=0\,,x_{t=0}=x_0,\ \dot{x}_{t=0}=0 \tag{1}$$

in which the matrices $\boldsymbol{M}$, $\boldsymbol{C}$ and $\boldsymbol{K}$ are the mass, damping, and stiffness matrix of the structure, respectively; $\ddot{x}$, $\dot{x}$ and x are the acceleration, velocity, and displacement vector of the structure, respectively; $\boldsymbol{x}_{t=0}=\boldsymbol{x}_0$ indicates the initial displacement at time $t=t_0$ for the free vibration; and $\boldsymbol{0}$ is a zero vector.

The discrete time solution of the state equation (1) can be written as

$$Z_k = e^{AT} Z_{k-1},\ \left(k=1,\cdots,K\right) \tag{2}$$

in which Z_k and Z_{k-1} are the state vectors at time instants, kT and $(k-1)T$, respectively.

Consider a linear, viscously-damped object truss structure shown in Figure 1 whose parameters are to be identified. To facilitate the whole parametric identification process, a reference structure and a number of associated structures that have the same overall dimension and topology as the object structure are created, and the SENN and PENN are established and trained based on the reference structure and associated structures.

The proposed DSPI strategy is carried out in three steps. In Step 1, the SENN is constructed and trained using the time series of free vibration-induced macro-strain responses of the reference structure under a certain predetermined initial condition.

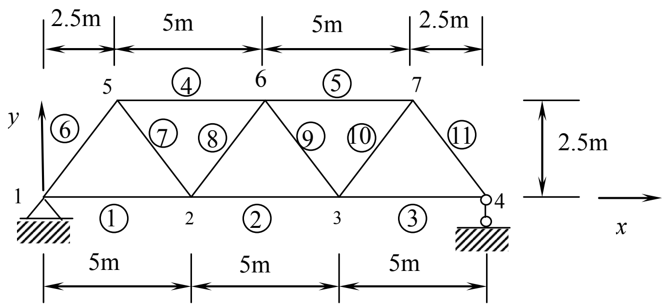


Fig. 1. Truss structure and macro-strain measurement.

Equation (2) indicates that, for the reference structure, the displacement response at time step k is uniquely and completely determined by the displacement and velocity at time step *k-1*. Moreover, the velocity response at time step *k-1* is related to the displacement change over the time interval from time steps *k-2* to *k-1*. Since the strain response at a certain time step is definitely determined by the displacement response at the same time step, the strain response at time step k is fully determined by the strain responses and at time steps *k-1* and *k-2*. Therefore, if the strain vectors ε_k and $\varepsilon_{k-1}, \varepsilon_{k-2}$ are selected as the output and input of the SENN, respectively, the mapping between the input and output is unique. The SENN trained to represent the mapping between the strain vector at time steps *k-2*, *k-1* and k of the reference structure is a non-parametric modeling for the reference structure and can be used to forecast the strain vector of the reference structure step by step as described in the following equation,

$$\varepsilon_k^f = SENN_\varepsilon(\varepsilon_{k-2}, \varepsilon_{k-1}) \quad , \quad (k = 2, \quad \cdots, \quad K) \tag{3}$$

where $SENN_\varepsilon$ means the SENN for the non-parametric identification of the reference structure; ε_k^f is the forecast strain at time step k by the trained SENN.

In Step 2, consider M associated structures that have different structural parameters from the reference structure in Step 1. On one hand, the free vibration-induced strain responses of an associated structure under the same initial condition as used in Step 1 can be calculated with the numerical integration. On the other hand, the strain responses can be predicted from the SENN trained for the reference structure according to Equation (3). Since the parameters of the associated structure differ from those of the reference structure, the predicted strain responses are quite different from those computed by numerical integration. In this paper, an evaluation index called the root-mean-square prediction difference vector (RMSPDV) of strain according to each associated structure is employed[13, 14]. Similar to the considerations on mass in most of the common identification studies in civil engineering, in this study, the mass of the structure assumed to be known and constant. Therefore, the evaluation index is then completely determined by the stiffness and damping matrix of the associated structure and can be described by the following functional relation:

$$RMSPDV_m = f(K_m, C_m) \tag{4}$$

So if the inverse of the function in equation (4) is known, structural parameters can be determined according to the evaluation index EI_m. For this purpose, the PENN is constructed and trained to describe the inverse relation between the evaluation index and the structural parameters:

$$(K_m, C_m) = PENN(RMSPDV_m) \quad (5)$$

Data patterns consisting of structural parameters of those associated structures and the corresponding RMSPDVs are used to train the PENN. After the PENN has been successfully trained, it will be applied in Step 3 into the object structure to forecast the structural parameters with RMSPDV of strain as the input. The macro-strain measurements of the reference structure, associated structures are determined by numerical integration. In practice, the strain measurements of the object structure can be measured with long-gauge FBG strain sensors or other sensors mounted on the structure members with sampling rate of 100 Hz, which is consistent with most of the current FBG interrogation systems. They are considered available in this numerical simulation study by Newmark integration with integration time step of 0.002 sec.

2.2 Implementation Scheme

In this study, it is assumed that the damping matrix of the reference structure, associated structures and object structure can all be characterized by the Rayleigh damping theory. The damping matrix of a structure *m* can then be expressed in the following form,

$$C_m = a_m M_m + b_m K_m \quad (6)$$

where a_m and b_m are the Rayleigh damping coefficients of the structure *m*.

In general, direct stiffness identification of the *N* members will usually reduce the total number of unknowns of the stiffness matrix of a structure. In the case of a truss structure, Equation (5) can be rewritten in the following form,

$$\left((k_1, \cdots, k_n, \cdots k_N)_m, a_m, b_m\right) = PENN(RMSPDV_m), \quad (m = 1, \quad \cdots, \quad N_m) \quad (7)$$

3. NUMERICAL ILLUSTRATION

3.1 Description of the Object Structure

The two-dimensional truss structure with 11 members and 7 joints shown in Figure 1 is treated as the object structure with a total of 11 degrees of freedom. For parametric identification of the object structure, the strain response under a predetermined strain initial condition can be calculated from strain measurements by FBG sensors or other strain sensors from monitoring system. Suppose one sensor is mounted on the surface of each member, a total of 11 strain measurement time series can be provided. For the sake of discussions, the stiffness scaling factor (SSF) and damping coefficient scaling factors (DCSFs) are defined as the ratios of the stiffness and damping coefficients of the object structure to those of the reference structure. One object structure is investigated here. The SSFs and DCSFs of the object structure are given in Table 1.

The parameters of a reference structure can be estimated from the as-built design drawings of the object structures. The modulus of elasticity, area of cross section and density of all members of the reference structure are 229.8GPa, $1.935\times10^{-3}m^2$ and $7800kg/m^3$, respectively. The lumped mass at joints 2, 3, 5, 6 and 7 is 15,000 kg, respectively. The first two natural frequencies of the reference structure are 2.651Hz and

5.577Hz, respectively. The first two mode damping ratios of the reference structure are assumed to be 0.1% and 0.2%, respectively. The Rayleigh damping coefficients can be respectively calculated to be $a = 2.122 \times 10^{-3}$ sec^{-1} and $b = 1.124 \times 10^{-4}$ sec.

Table 1. Parameters of the object structure

SSF											DCSF	
1	2	3	4	5	6	7	8	9	10	11	α	β
0.8	0.9	1.0	0.9	1.0	0.9	0.9	1.0	0.9	1.0	1.0	0.9	1.0

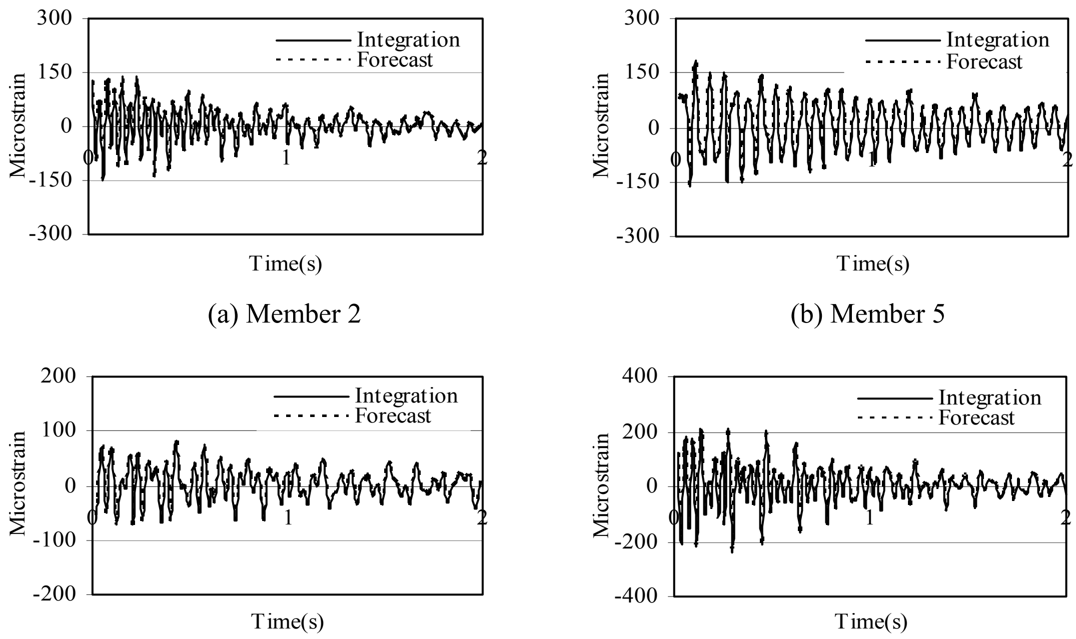
Without loss of any generality, the initial displacements at 11 degrees of freedom are assumed to be

$$\{X_0\} = 0.0005 \times \{1 \quad 1 \quad -1 \quad -1 \quad -1 \quad -1 \quad 1 \quad 1 \quad 1 \quad -1 \quad 1\}^T (m) . \qquad (9)$$

The corresponding strain initial conditions of the 11 members are as follows, 100, -200, 0, 200, -200, 0, 200, 0, 0, 200 and 100 $\mu\varepsilon$.

3.2 Nonparametric Identification for the Reference Structure with SENN

As described above, the structural macro-strain response at time step *k* can be completely determined by those at time step *k-2* and *k-1*. The input layer of the SENN includes the macro-strain responses at time step *k-2* and *k-1* for every member of the truss structure. The number of neurons in the hidden layer is the same as that in the input layer. The neuron in output layer represents the forecast macro-strain responses at time step *k*. Therefore, for the truss structure with 11 members, the input, hidden and output layers have 22, 22 and 11 neurons. SENN is off-line trained with the training data sets composed of the simulated macro-strain responses of the reference structure.



(a) Member 2 (b) Member 5

(c) Member 8 (d) Member 9

Fig. 2. Exact versus predicted strain time histories of the reference structure.

From the first 2 seconds of free vibration-induced strain responses under the initial displacement, 198 patterns of training data sets are constructed. The entire off-line training process takes 30,000 epochs. To examine the accuracy of the SENN in time domain, comparisons for member 2, 5, 8 and 9 are made in Figure 2 between the macro-strain responses from 0.03 to 2.0 seconds determined from the Newmark-method and those predicted by the above trained SENN. It is clearly seen that the two series of time histories match very well.

To provide a quantifiable measure for the prediction by the SENN, the root-mean-square (RMS) error of macro-strain corresponding to each truss member are given in Table 2. It is demonstrated from Table 2 and Figure 2 that the maximum RMS error is within 3.5% the RMS value of the macro-strain response. Neural network provides a novel way to model the reference structure using strain measurements.

Table 2. RMS error of macro-strain of each truss member of the reference structure

Member	RMS value of strain by Newmark-β(10^{-6})	Absolute error in RMS (10^{-6})	Relative error in RMS (%)
1	32.91	0.80	2.43
2	46.90	0.83	1.77
3	43.16	0.47	1.09
4	45.90	0.75	1.63
5	66.91	1.12	1.67
6	28.93	0.78	2.71
7	67.50	2.35	3.48
8	30.25	0.59	1.94
9	73.73	2.26	3.07
10	61.59	0.88	1.43
11	60.67	0.78	1.29

3.3 Training of PENN for Stiffness and Damping Coefficients Identification

The input to the PENN is the components of the RMSPDV corresponding to the macro-strain measurement of each truss member, and the output is the stiffness of each truss member and the damping coefficients of the object truss structure. For the object structure with 11 truss members, the PENN thus has 11 input neurons and 13 output neurons representing the stiffness of each member and the structural damping coefficients. The number of neurons in the hidden layer is selected to be four times the number of the neurons in the input layer.

To generate training patterns, a significant number of associated structures with different structural properties are considered and their free vibration responses under the initial displacement are computed with the Newmark integration method. The RMSPDV of macro-strains between each associated structure and the output of the SENN can then be obtained. Because neural networks can describe complex mapping with satisfied accuracy within a certain space that is covered by the training patterns by interpolation and the performance of neural networks for extrapolation is not guaranteed, it is important to determine the possible range of the interested parameters. Suppose stiffness decrease of each truss element is within 20% of it of the reference structure and damping coefficients have a change within 20% of the reference structure.

The number of the possible structures with different structural parameters within the assumed interested space is infinite. It is critically important to prepare training patterns or data sets with proper sizes from the interested space. Selection of a suitable number of the training patterns from an interested space that includes unlimited points is still an open problem. In this study, 800 associated structures other than the object truss structure shown in Table 1 are randomly selected from the interested space to construct training patterns for PENN training. Each training pattern is composed of a RMSPDV and its corresponding structural parameters. The training process took 30,000 epochs using the adaptive error back-propagation algorithm.

3.4 Parametric identification results with DSPI strategy

After having been trained, the PENN can be adopted to identify the structural parameters directly from 2 seconds of the time series of macro-strain responses. Two seconds of the free vibration-induced macro-strain measurements from the object structure are directly inputted to the SENN and the PENN. The rations of exact stiffness of each truss member and damping coefficients to them of the reference structure and the relative error are shown in Figure 3. The average relative error for the entire structure is less than 4% even though the object structure is not included in the training patterns.

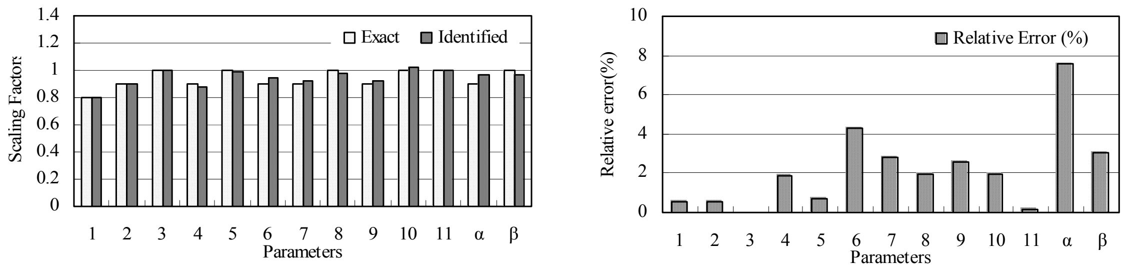


Fig. 3. Parametric identification results for the object structure

4. CONCLUDING REMARKS

The performance of the strategy was illustrated with an engineering truss structure. Based on numerical simulations, the following conclusions can be drawn:

1. The free vibration-induced macro-strain response at current time step can be successfully forecast by a non-parametric identification model, strain-based emulator neural network, using the strain responses at the two previous time steps.

2. The parametric evaluation neural network trained with a number of training patterns that are randomly selected from the interested space can accurately identify the parameters of object structures, even if the object structures are not included in the selected training patterns. The average relative error in identified parameters is less than 3% when strain measurement is not contaminated with noise.

3. The proposed strategy does not involve any formulation of eigenvalue analysis, eigenvalue or mode shape extraction from the measurements. Use of directly-measured strain responses and the parametric evaluation neural network allows the parameters of engineering truss structures to be identified using 2 seconds of macro-strain

measurements. Therefore, the proposed strategy provides a viable tool for near real-time parametric identification for structural health monitoring.

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