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Element Level Parametric Identification Using Axial Macro-Strain Time Series

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Abstract: The increasing use of advanced sensing technologies for strain measurements necessitates the development of strain-based identification methodologies. In this study, a three-step neural network strategy, called direct soft parametric identification (DSPI), is presented to identify the member stiffness and damping parameters of a truss structure directly from free vibration-induced strains. The rationality of the proposed 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 is examined.

Key-Words: structural identification, free vibration, strain, performance, artificial neural network, stiffness, damping coefficients

1 Introduction

Many of civil infrastructures are now deteriorating due to aging, misuse, lacking proper maintenance, and, in some cases, overstressing as a result of increasing load demands and changing environments. It is critical to evaluate their current reliability, performance and condition for the prevention of potential catastrophic events. Due to its ability to continuingly report performance of a civil infrastructure, structural health monitoring is an emerging technology that could play an essential role in realizing a sustainable society. An integral component of such a system is the development of computationally-efficient system identification strategies. The identification of materials and structural properties can generally be categorized into two groups: local and global methodologies. The most widely used global identification methodology is based on vibration measurements [1-2].

On one hand, advanced new sensors such as distributed optical fibers and piezoelectric sensors are being developed to continuously monitor the structural strain distribution in recent years [3]. The rapid development of these strain sensing techniques necessitates the development of a new structural identification methodology based on strain measurements.

On the other hand, 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 [4].

Although several neural-network-based strategies are available for qualitative evaluation of damages that may have taken place in a structure [5], it was not until recently that a quantitative way of detecting damage with neural networks has been proposed. Yun et al. presented a method for estimating the stiffness parameters of a complex structural system by using a back-propagation neural network with natural frequencies and mode shapes as inputs [6]. Unlike any conventional system identification technique that involves the inverse analysis with an optimization process, those strategies proposed by Xu et al. and Wu et al. with the direct use of dynamic responses can give the identification results in a substantially faster way and thus provide a viable tool for the on-line identification of structural parameters for an real-time monitoring system [7, 8].

This study is aimed at the development of a strain-based identification strategy for the structural monitoring. The stiffness parameter of each structural member and the damping coefficients of the structural system are to be identified. The performance of the three-step direct soft parametric identification (DSPI) methodology is evaluated with a tower type of truss structure with a known mass distribution.

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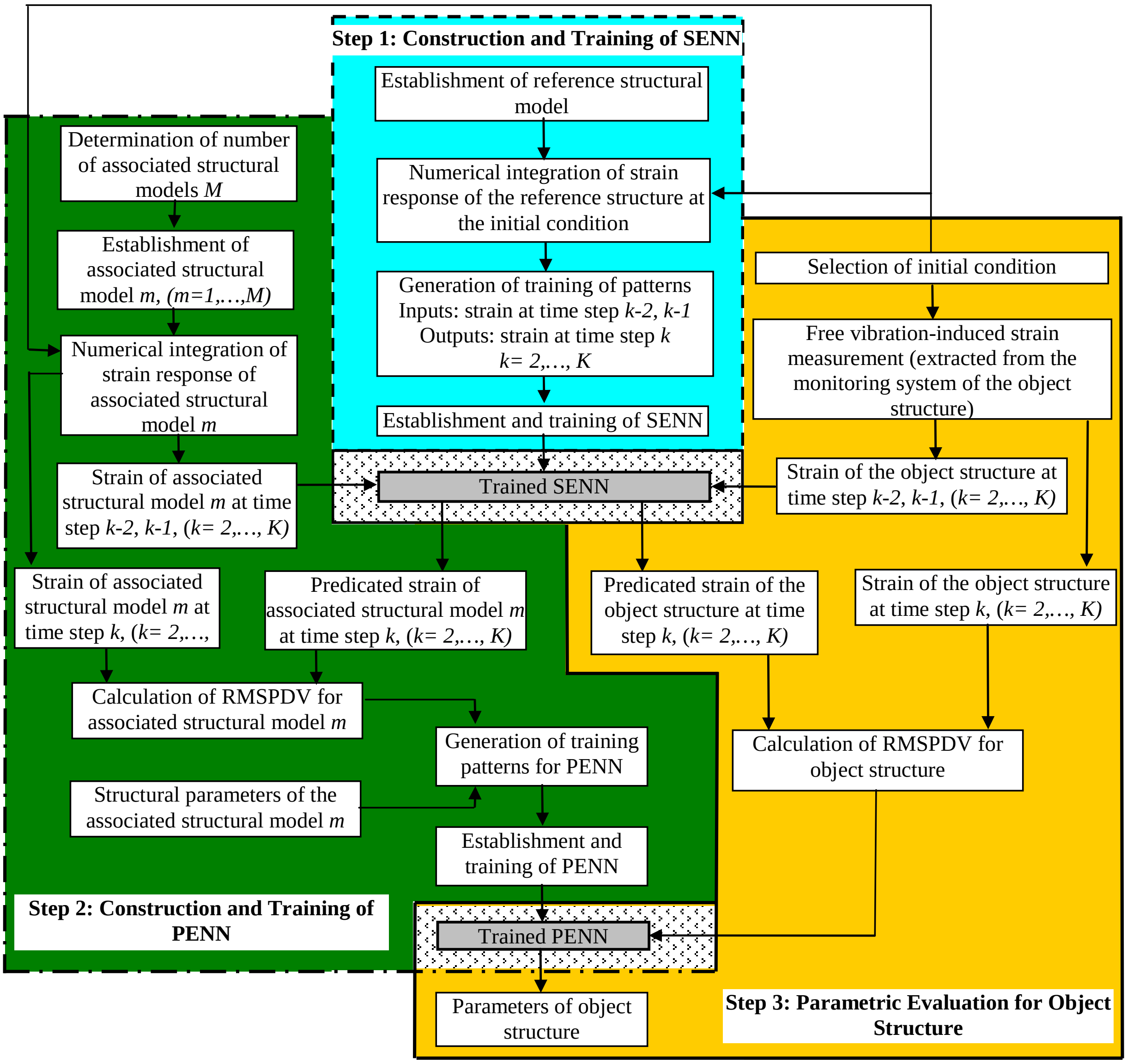

Fig. 1: Parametric identification modeling based on neural networks with dynamic macro-strain responses

2 Member Level Parametric Identification Using Macro-strain Measurement

A linear, *N*-DOF viscously-damped existing structure is referred to an object structure. To facilitate the member level 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. The member level parameter identification strategy is carried out by three steps as shown in Fig. 1.

In Step 1, a strain-based emulator neural network (SENN) is constructed and trained using the time series of free vibration-induced macro-strain responses of the reference structure under a certain initial condition. Under an initial displacement X_0 and a zero velocity, structural free vibration can be described by,

$$M\ddot{X}+C\dot{X}+KX=0,\ X_{t=0}=X_0,\ \dot{X}_{t=0}=0 \quad (1)$$

where the matrices $\boldsymbol{M}$, $\boldsymbol{C}$ and $\boldsymbol{K}$ are mass, damping, and stiffness matrix, respectively; and $\ddot{X}$, $\dot{X}$ and X are the acceleration, velocity, and displacement vector, respectively.

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

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

in which $\boldsymbol{Z_k}$ and $\boldsymbol{Z_{k-1}}$ are the state variables at time instants, kT and $(k-1)T$, respectively; and $\boldsymbol{A}$ is the system matrix.

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 determined by the displacement change over the time interval from time step *k-2* to *k-1*. For a truss structure, the strain response of a member at a certain time step is definitely determined by the displacement responses at its two ends at the same time step, therefore, the strain response at time step *k* is fully determined by the strain responses at time steps *k-1* and *k-2*. A SENN can be trained to represent the mapping between the strain vector at time step *k-2*, *k-1* and *k* of the reference structure and can be a non-parametric modeling of the reference structure as described in the following equation,

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

where 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 *m* at time step *k* under the same initial condition as used in the reference structure can be determined by numerical integration. On the other hand, a predicted strain responses can be determined according to Equation (3). It is expected that the predicted responses are quite different from those computed by numerical integration because of the parameter difference. Their difference vector at time step k can be evaluated by

$$E_{m,k} = \left\{ e_{m,k}^{(1)} \quad \cdots \quad e_{m,k}^{(j)} \quad \cdots \quad e_{m,k}^{N_m} \right\}^T = \varepsilon_{m,k}^f - \varepsilon_{m,k},$$

$$(m = 1, 2, \ldots, M, \quad j = 1, \cdots, N_m, \quad k = 2, \cdots, K) \quad (4)$$

where N_m represents the total number of structural members which strain responses are measured. The superscript *T* in equation (4) denotes the transpose of a vector. Similar to the previous studies of Xu et al. [8], corresponding to the associated structure *m*, an evaluation index called the root-mean-square prediction difference vector (RMSPDV) of strain is adopted. It is obvious that RMSPDV depends on the structural parameters of the associated structure m and should be a function of structural mass, stiffness and damping matrices. The mass matrix is considered as a known constant in this study, the evaluation index is then completely determined by K_m and C_m. The parametric evaluation neural network (PENN) is constructed and trained to describe the mapping between the evaluation index and the structural parameters:

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

After the PENN has been successfully trained with the associated structures in Step 2, it will be applied in Step 3 into the object structure to forecast the structural parameters with inputs, RMSPDV, determined from the trained SENN and the strain measurements of the object structure.

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. In general, direct identification of the stiffness matrix of a structure is inefficient due to its complex geometry and member connectivity. However, the direct identification of member stiffness will reduce the total number of unknowns. Equation (5) can be rewritten in the following form,

$$\left((k_1, \cdots, k_n, \cdots k_{N_m})_m, a_m, b_m \right) = PENN(\{EI\}_m),$$

$$(m = 1, \quad \cdots, \quad N_m) \quad (6)$$

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. They are considered available in this numerical simulation study by numerical integration.

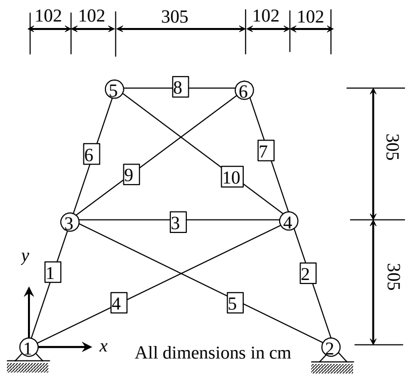

Fig. 2: Truss structure

Table 1. The physical properties for all members of the reference structure

Modulus of elasticity	229.8 GPa
Area of cross section	19.35×10^{-6} m^2
Density	7800kg/m^3
Lumped mass on joint 3, 4, 5, 6	20,000 kg

3. Numerical Illustration

3.1 Object Structure

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The two-dimensional truss structure with 10 members and 6 joints shown in Fig. 2 is treated as the object structure. Two joints are pin-supported at the bottom of the truss structure. It has a total of 8 degrees of freedom. Considering one sensor is mounted on the surface of each member, a total of 10 strain measurement time series can be provided by the sensing system. The material density and area of cross section of every member and the lumped mass at joints 3, 4, 5, 6 of a reference structure that can be estimated from the as-built design drawings of the object structures are shown in Table 1. The first two natural frequencies of the reference structure are 4.627Hz and 8.075Hz, respectively. The first two mode damping ratios are assumed to be 0.1% and 0.15%, respectively. The Rayleigh damping coefficients can be respectively calculated to be $a = 0.012\ \mathrm{sec}^{-1}$ and $b = 5.44 \times 10^{-5}$ sec.

Without loss of any generality, the initial displacements at 8 degrees of freedom are assumed to be

$$\{X_0\} = 0.0005 \times \{1 \quad 1 \quad -1 \quad -1 \quad -1 \quad -1 \quad 1 \quad 1\}^T (m) \qquad (7)$$

The free vibration macro-strain responses of the reference, associated and object truss structures under the initial condition can be solved by numerical integrations with the Newmark method. The integration time step used is 0.002 sec and the sampling rate is 100 Hz, which is consistent with most of the current FBG interrogation systems.

3.2 Nonparametric identification for the reference structure with SENN

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, the input, hidden and output layer includes 20, 20 and 10 neurons, respectively.

From the first 2 seconds of free vibration-induced strain responses under the initial displacement in Equation (7), 198 patterns of training data sets are constructed. Based on the error back-propagation algorithm, SENN is off-line trained with the training data sets composed of the simulated macro-strain responses of the reference structure. At the beginning of training, the connection weights between two adjacent layers are initialized with small random values. SENN can be trained to achieve a desired accuracy for modeling the dynamic behavior of the reference structure. The entire off-line training process takes 30,000 epochs. An adaptive learning schedule is adopted, in which the learning rate and momentum are chosen to be high (0.8 and 0.6) at the early stage of training and low (0.5 and 0.3) at the following time instances.

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 that the maximum RMS error is within 5% the RMS value of the corresponding macro-strain response. The nonparametric model of the reference structure, SENN, is therefore sufficiently accurate.

3.2 Training of PENN for stiffness identification

3.2.1 Evaluation index and PENN architecture

For the purpose of parametric identification, it is a critical task to establish a mathematical model for mapping from the RMSPDV to the structural parameters. The PENN is organized to describe the mapping. The input to the PENN is the components of the RMSPDV corresponding to the macro-strain response 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 shown in Fig. 2, the PENN thus has 10 input neurons and 12 output neurons. The number of neurons in the hidden layer is selected to be four times the number of the neurons in the input layer.

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

Member	RMS value of strain by integration(10^{-6})	Absolute error in RMS (10^{-6})	Relative error in RMS (%)
1	87.4	2.1	2.4
2	80.4	1.6	2.0
3	84.7	0.9	1.1
4	39.8	1.8	4.5
5	40.5	1.8	4.6
6	105.6	3.3	3.2
7	95.4	1.9	2.0
8	150.6	2.4	1.6
9	63.5	0.9	1.3
10	66.6	1.2	1.8

3.2.2 Generation of training patterns

To generate training patterns, a significant number of associated structures with different structural properties are considered and their free vibration

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responses under the initial displacement in Equation (20) are computed with the Newmark 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 damage scenarios within the assumed interested space is infinite.

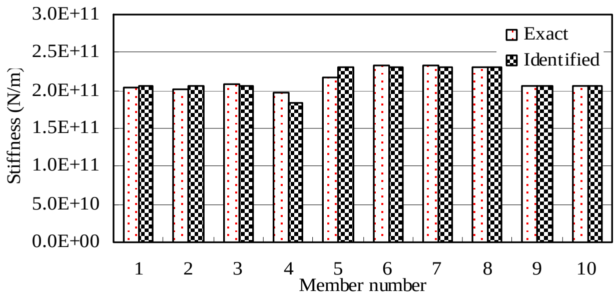
It is critically important to prepare training patterns or data sets with proper sizes from the interested space. In general, the number of training patterns must be large enough to represent the relationship between the RMSPDVs and their corresponding parameters while, for computation efficiency, the number of training patterns ought to be reasonably small. An appropriate tradeoff needs to be established in preparation of training patterns. Moreover, the preparation of training patterns for the PENN training is generally time-consuming, especially for large-scale infrastructures. 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 three object truss structures 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.

3.2.3 Training of PENN

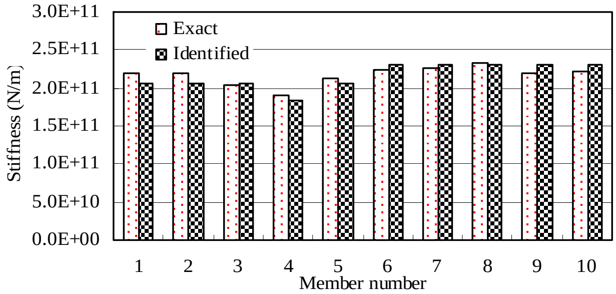
Each of the training patterns prepared above is used once for training of PENN at an epoch. The data is normalized between the ranges of 0 to 1 to make sure that all the data contribute evenly and to fulfill the criteria of the sigmoid transfer function. The training process took 30,000 epochs to learn the pattern presentation using the adaptive error back-propagation algorithm.

3.3 Parametric identification results with DSPI strategy

After having been trained, the PENN can be adopted to identify the structural parameters directly from 2s of the time series of macro-strain responses. The proposed strategy differs from other traditional parametric identification techniques that require inverse analysis; it can give structural identification results rapidly by feed-forwarding the parallel computation of neural networks when several seconds of time series are available. This characteristic makes the proposed technique very attractive for near real-time damage diagnosis of structures in the frame-work of structural health monitoring.



(1) Object structure 1



(2) Object structure 2

Fig. 3: Stiffness identification results

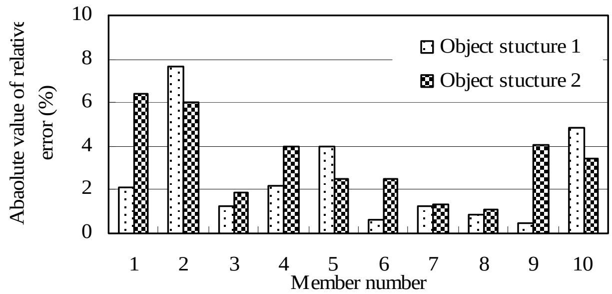


Fig. 4: Absolute values of relative identification error distribution

Table 3: Damping coefficients identification results

			Object structure 1	Object structure 2
Damping coefficients	a (10^{-2})	Exact	1.14	1.14
		Identified	1.20	1.20
	b (10^{-5})	Exact	5.18	5.17
		Identified	5.44	4.90
Average of absolute values of relative error (%)			2.99	3.66

2s of the free vibration-induced macro-strain measurements from the two object structures are directly inputted to the SENN and the PENN. The stiffness of each truss member is identified as shown in Figs. 3 and 4. Table 3 shows the damping coefficients identification results. It can be found that the average relative error of the estimation for the entire structure is less than 4% even though the training pattern for the object structure is not included in the training patterns utilized above.

4 Conclusion and discussion

A three-step novel neural networks based strategy has been developed for the identification of structural parameters, member stiffness and system damping coefficients of a truss structure, with direct use of free vibration-induced macro-strain responses.

1. The free vibration-induced macro-strain response at the current time step can be successfully forecast by a non-parametric identification model, strain-based emulator neural network, based on the strain responses at the two previous time steps. The rationality and theory basis for the construction of the strain-based emulator neural network and parametric evaluation neural network are explained.

2. The parametric evaluation neural network 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 5%.

The proposed strategy does not involve any formulation of eigenvalue analysis for the reference structure and the associated structures, eigenvalue and mode shape extraction from the measurements or any optimization process that is required to solve inverse problems with most identification algorithms. Use of directly-measured vibration responses and the parametric evaluation neural network allows the parameters of engineering truss structures to be identified with 2s of macro-strain measurements. Therefore, the proposed strategy provides a viable tool for near real-time parametric identification or for on-line structural health monitoring.

The proposed strategy is based on free vibration-induced strain measurements, therefore, it is applicable for on-line identification of structures instrumented with long-term monitoring system and excited by ambient loads that can be modeled as stationary zero-mean Gaussian white time series from which structural free vibration-induced strains can be extracted by RD method. In the case of engineering structures where loads can not be modeled as stationary zero-mean Gaussian white time series, direct free vibration experiment is an alternative to acquire the free vibration-induced strain measurement, and the strategy proposed in this paper is also applicable.

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