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A novel unsupervised deep learning model for global and local health condition assessment of structures

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ABSTRACT

A methodology is described for global and local health condition assessment of structural systems using ambient vibration response of the structure collected by sensors. The model incorporates synchrosqueezed wavelet transform, Fast Fourier Transform, and unsupervised deep Boltzmann machine to extract features from the frequency domain of the recorded signals. A probability density function is used to create a structural health index (SHI). This index can be used to assess both the global and local health conditions of the structure. A beauty of the proposed model is that it does not require costly experimental results to be obtained from a scaled version of the structure to simulate different damage states of the structure. Only ambient vibrations of the healthy structure are needed. In the absence of ambient vibrations, they can be simulated stochastically using structural properties and the probability theory. The effectiveness of the proposed model is illustrated employing experimental data obtained on a shake table in Hong Kong.

1. Introduction and literature review

Health monitoring of large and complex structures is considered a key high technology at the forefront of structural engineering research not only for civil structures but also aerospace and mechanical structures [3,38,39,34,35]. Significant research has been reported mostly on vibration-based health monitoring [43,34,35,19] but also on vision-based health monitoring [40]. Review of the recent literature can be found in a number of article such as Sirca and Adeli [36], Qarib and Adeli [27], Amezquita-Sanchez and Adeli [6], and Perez-Ramirez et al. [26].

Machine learning, a key technology in the 21st century, can be divided into supervised learning such as backpropagation neural networks [2], Support Vector Machine (SVM) [42,8,12], the enhanced probabilistic neural networks [4] and recently developed Neural Dynamics Classification algorithm [31] and unsupervised learning such as Self Organizing Map [7], Restricted Boltzmann machine (RBM) [37], Deep Boltzmann Machine (DBM) [17,41], and deep convolutional neural networks [11].

Recently, authors presented a new model to detect for global health monitoring of large structures such as highrise building structures based on integration of synchrosqueezed wavelet transform (SWT) [14], an unsupervised Restricted Boltzmann Machine (RBM) [37], and a new classifier developed by the authors called neural dynamics classification (NDC) algorithm [31]. The model requires experimental data on a scaled model of the structure to simulate different healthy and various damage states. The model was validated using the data obtained from a 1:20 scaled 38-story reinforced concrete building structure on a shake table in Hong Kong shown in Fig. 1a. A high maximum average accuracy of 96% was reported [30].

In this paper, a novel unsupervised learning model is presented for both global and local condition assessments of structural systems using ambient vibration response data of the structure collected by sensors. The model employs the SWT to denoise the measured signals and an unsupervised *deep* RBM (DRBM) to extract features from the frequency domain of the signals [17,29,32]. A probability density function is used to propose a structural health index (SHI) similar to development of indices for diagnosis of diseases [1]. The probability density function used in this research is derived from the concept of Bayesian inference [22,9,10] where the conditional probability of a new record of vibration given other records is computed. The conditional probability addresses the similarity of the two records known as likelihood in statistics [20].

The effectiveness of the proposed model is illustrated using the data

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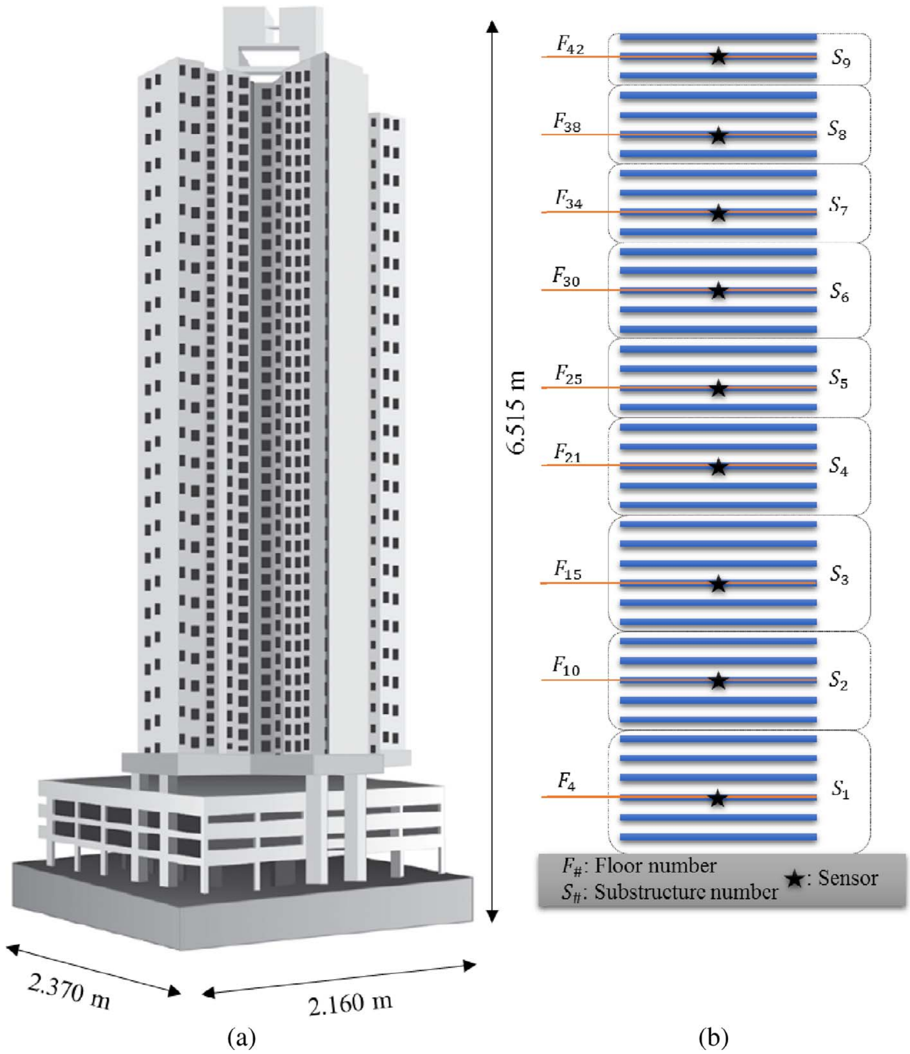

Fig. 1. (a) The scaled 38-story residential highrise building structure in Hong Kong [5,5,6]; and (b) the substructures and locations of sensors along the height.

obtained from the 3D 1:20 scaled 38-story reinforced concrete building structure [23] used in the author's earlier work [30].

2. Proposed algorithm

2.1. Requirements of the model

In contrast to the recent model developed by the authors [30], the proposed model does not require damage simulation of a scaled version of the structure. The input consists of a set of records obtained from the healthy state of the structure and another set of records with unknown health states. The model extracts information from both healthy and unknown sets to determine the health states of the unknown set. The healthy records are low-intensity ambient vibrations of the structure at least in one planar direction in the healthy state in the form of time series signals. Ambient vibrations can be due to wind, traffic, or human/pedestrian activities. Such vibrations are usually recorded by placing a few sensors on preselected locations such as floors of a highrise building structure.

The proposed model employs a substructuring scheme. Each floor of a highrise building structure and a number of its adjacent floors form a substructure. Optimum selection of substructures and sensor locations are important subjects in the field of structural system identification and health monitoring but outside the scope of the current paper. In the absence of real ambient vibrations for the healthy state, one can simulate them computationally using the probability theory. In the proposed algorithm, a structure is divided into S substructures with sensors located at least on one floor of each substructure. As an example, the 38-story reinforced concrete building structure shown Fig. 1a is divided into 9 substructures denoted as S_1, S_2, …, and S_9 with corresponding sensors located at floor numbers 4, 10, 15, 21, 25, 30, 34, 38, and 42, respectively.

2.2. Five steps performed on each substructure to calculate the local SHI

In the proposed model, 5 steps are performed for each substructure shown in Fig. 2. In step 1, first each healthy recorded time series signal of T_H seconds duration with sampling frequency of F_H Hz (totaling $T_H \times F_H$ discrete points for the signal) corresponding to a substructure is divided into N_H vectors of recorded acceleration, $\boldsymbol{H}_i$ where $i \in \{1,2,...,N_H\}$, each with $L = \frac{T_H \times F_H}{N_H}$ terms. These vectors include information about the healthy state of that substructure. Next, unknown recorded time series signal of T_U seconds duration with sampling frequency of F_U Hz (totaling $T_U \times F_U$ discrete points for the signal) corresponding to that substructure is divided into N_U vectors, $\boldsymbol{U}_j$ where $j \in \{1,2,...,N_U\}$, each with $L = \frac{T_U \times F_U}{N_U}$ terms. These vectors include information about the current unknown state of that substructure. Usually, $N_H = N_U$, $T_H = T_U$, and $F_H = F_U$. If not, N_H and N_U are selected such that $L = \frac{T_H \times F_H}{N_H} = \frac{T_U \times F_U}{N_U}$. It is postulated that with proper selection of N_H and N_U, L will be large enough such that an ample number of features is encoded and is traceable in every $\boldsymbol{H}_i$ and $\boldsymbol{U}_j$ for accurate representation of a specific healthy or damage state in a substructure.