Application of Principal Components Analysis Method to Wireless Sensor Network Based Structural Monitoring Systems

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ABSTRACT

Typical wireless sensor networks used in structural monitoring are continuous types wherein data transmission is progressive at all time that may include irrelevant and insignificant data and information. Continuous types of wireless monitoring systems often pose problems of handling large-sized data that may deteriorate the performance of the system. The proposed method is to suggest an event-triggered monitoring system that captures and transmits relevant data only. An error signal generated by the Principal Components Analysis (PCA) is utilized as an index for event detection and selective data transmission. With this new monitoring scheme, the remote server is relieved of unwanted data by receiving only relevant information from the wireless sensor networks. The performance of the proposed scheme was verified with simulation studies.

Key Words : Principal components analysis, structural monitoring, wireless sensor network, structural vibration, event detection, selective data transmission

Introduction

Real-time monitoring of civil infrastructures such as bridges and buildings is critical to the long-term operational cost and safety of aging structures. Knowledge of the structure's health and behavior, load bearing capacity, and remaining life is the primary goal of Structural Monitoring (SM). Recently, interest has been growing in SM which has a potential to extend the lifetime and prevent sudden catastrophic failures of civil and mechanical systems through information- based maintenance and repair.

Sensor and data acquisition systems are the essential parts of a SM. A new trend in SM is towards the use of sensor networks, which are composed of a large number of sensors. A combination of information from sensor network can provide a high- resolution, multi-dimensional information of large-scale structural systems.

Generally, transmitting large-sized sensor data in a wireless communication puts a high demand on its communication bandwidth. Furthermore, data users might be interested in abnormal situations such as earthquake etc., with different resolution over different time period. Therefore, a new monitoring scheme is required, which might provide an alternative solution to alleviating the limited communication bandwidth and provide users the flexibility to retrieve selective sensor data in case of abnormal events.

Principal Components Analysis (PCA) is a useful statistical technique that has gained popular application in the fields such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension [5-6, 14]. The main advantage of PCA is that it can represent correlated multi-dimensional information by significantly reducing the dimension while retaining the most important information that is the principal components of the signal [11]. Ogaja et al. [7] use the PCA method to reduce the amount of wavelet transformed global positioning system (GPS) data. The PCA method was also used by Ikhlas et al. [2] to extract critical features from images of a cracked bridge. Recently Ruan et al. [13] used PCA for the compression of wind-induced surface pressure data. The use of PCA in these applications was motivated by the information overloading problem associated with raw data and critical features.

The use of PCA has found its way into wireless structural monitoring systems in the data retrieval and management processes and structural damage assessment where PCA has been used in typical functions of feature monitoring, progressive transmission and data compression, and fault diagnosis [1-2, 4-15]. Basharat et al. [1] proposed an event detection technique using a mean shift activity vector that assumes unnecessary data when the activity metric value is below a threshold value and

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detects between normal and abnormal vibration wherein the sampling frequency is adjusted from low to high. In their method [1], they only classify the data, but don't selectively compress the huge event data file. The proposed method by Li and Zhang [11] was just to provide data users with the flexibility to select data and retrieve data at multi-resolution levels but the calculation in their solution methods are complex. Typical proposed systems of event detection strategies [4, 8-11, 15] are obtained from progressive data collection and transmission.

In this study, PCA is applied to a new system of management and transmission of large volume of vibration sensor data in a wireless sensor network for the structural monitoring system with added feature of event detection and selective data recording and transmission. These vibrations can be the responses of a structure to extreme types of events such as strong winds, earthquake, and impulse responses.

With the utilization of PCA algorithms, a new scheme of enhanced SM is proposed in this work, in which raw sensor data are pre-classified as either ambient or significant according to the existence of events. Relevant sensor data can be easily selected and stored by comparison with a threshold value evaluated from normal ambient conditions. These significant sensor data within their periods of occurrence are then captured, compressed, and transmitted to the remote servers for reconstruction. The proposed system can effectively solve the communication problems usually encountered in a continuous or all-time monitoring by capturing and sending only relevant sensor data.

2. Fundamentals of Principal Component Analysis (PCA)

The basic idea of PCA is to derive new variables (principal components arranged in descending order of importance) that are linear combinations of the original variables and are uncorrelated to each other. Principal components are obtained by projecting the multivariate data vectors on the space spanned by the eigenvectors of the covariance matrix of the original data set. One of the advantages of PCA is its ability to describe the data using a small group of underlying variables while preserving as much of the relevant information as possible in the dimensionality reduction process.

Suppose that y_i are the measured time history vectors from a total number of p sensors, where $i = 1, 2, \ldots, p$, the data vector containing the p sensor measurements can be written as

$$Y = [y_1, y_2, \ldots, y_p] \tag{1}$$

The $p \times p$ covariance matrix Ω of Y can be calculated as

$$\Omega = E[YY^T] - E[Y]\,E[Y^T] \tag{2}$$

By taking a linear transform, the j th principal component of the original data set is

$$u_j = Y \cdot a_j \tag{3}$$

where $a_j = [a_{j1}, a_{j2}, \ldots, a_{jp}]^T$ is the eigenvector corresponding to the j th largest eigenvalue λ_j of the covariance matrix Ω. This can be rewritten in matrix form as

$$U = Y \cdot A \tag{4}$$

where $A = [a_1, a_2, \ldots, a_p]$ is a matrix consisting of eigenvectors of the covariance matrix as the column vectors and $U = [u_1, u_2, \ldots, u_p]$ contains the p principal components corresponding to p-dimensional original data.

The principal components can be used to reconstruct the original data by

$$\hat{Y} = U \cdot A^{-1} \tag{5}$$

Instead of using all the principal components to reconstruct data, we may represent the data in terms of only first few principal components. This will generally result in loss of information after inverse transformation. However, the eigenvectors of the covariance matrix Ω are arranged in such a way that the first few eigenvectors correspond to the directions with largest variances of the data. Therefore, the first few principal components carry the most significant amounts of information of the original data. The reconstruction error is defined as the difference between the original data and reconstructed data as,

$$e = Y - \hat{Y} \tag{6}$$

The detection index is the Squared Prediction Error (SPE) defined by,

$$d = e^T e \tag{7}$$

The SPE can be effectively used for detecting the normal and abnormal changes in the structural vibrations responses in an event-triggered monitoring process [8-9].

3. A New Type of Structural Monitoring System based on PCA

In this study, a new type of structural monitoring system based on PCA is proposed, with features of event detection and selective data recording, compression, and transmission. The system is hereby called an event-triggered monitoring shown in Fig. 1.

In an event-triggered monitoring system, only relevant sensor data are recorded and transmitted to the remote server in contrast to the continuous or all-time monitoring system. In a continuous (all-time) monitoring system, all sensor data are recorded at every second and are transmitted to the remote server at all times even during the no-event period as well as during the period of significant event occurrence.

The key point of the proposed algorithm is to use SPE in Eq. (7) as an index and indicator for the detection of changes from normal to abnormal situation as well as getting to know the time and period when such abnormal changes happens. In the event of abnormal structural behavior such as an earthquake, the SPE of the coming raw sensor data exceeds the predefined threshold value corresponding to normal conditions. The threshold value can be pre- calculated from normal sensor data which are considered to be irrelevant.

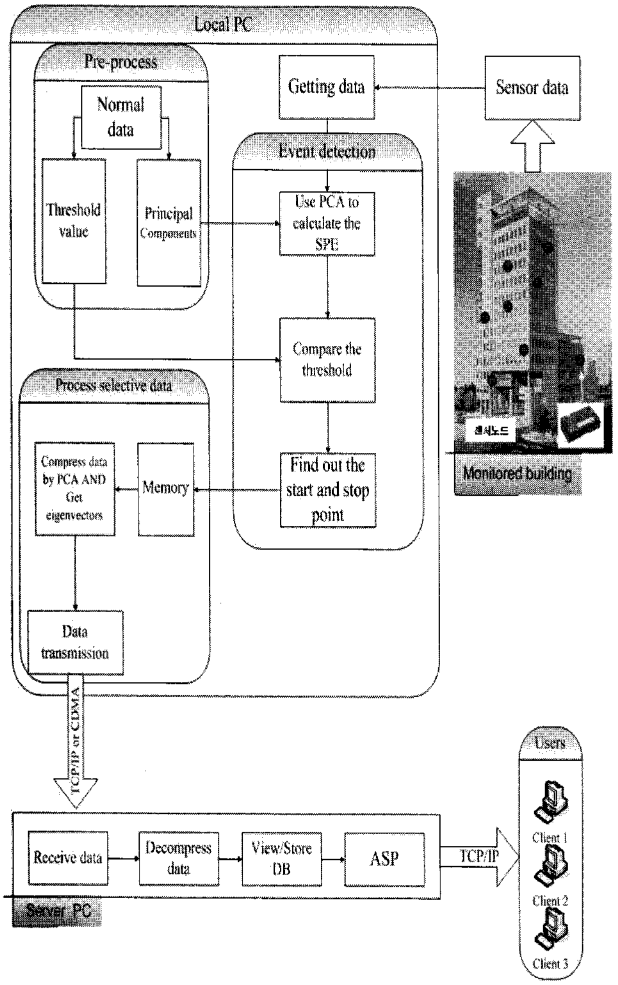

Fig. 1. The proposed system

The detailed procedure is described as follows:

STEP 1: Calculate eigenvalues and eigenvectors for the covariance matrix which is obtained from measurement data during some period of time under normal conditions. Some of the eigenvectors are selected as principle components and they can be used to calculate the detection index of the incoming sensor data. This step is called the 'Pre-process' stage in the proposed system.

STEP 2: Calculate the SPE for newly coming sensor data.

STEP 3: If SPE of newly coming data exceeds the predefined threshold value, data are successively stored into the internal memory until SPE goes back below threshold value.

STEP 4: The stored data in Step 3 are compressed by using PCA, and compressed data and its corresponding eigenvectors are transmitted to the remote server for reconstruction. In the server computer, compressed data can be effectively reconstructed by using the transmitted eigenvector.

Generally, sensor data from the sensor network are consolidated on the sink node at all the time. And they are processed for the detection of relevant event. By making use of the detection index calculated from Eq. (7) the occurrence of abnormal situation can be easily detected. Furthermore, the compressed value and its eigenvectors are sent to remote server to reconstruct the original data. All coming sensor data whose detection index is below the threshold value can be thought of as normal data which may be irrelevant and can be disregarded or neglected. On the other hand, the coming sensor data whose detection index is exceeding the threshold value means that the structure undergoes external excitation such as earthquake. These vibration responses are crucial to the state of the structure and are very relevant in order to evaluate its structural stability and integrity. In this case, the recorded sensor data are captured, compressed, and transmitted to the remote servers for evaluation along with their corresponding feature vectors and time periods of occurrence.

4. Simulation Study

In order to demonstrate the features of the proposed scheme, a simulation study was carried out. We consider a 15 story building and the vibration data are obtained from numerical finite-element model by using Finite Element Analysis (FEA) program as shown Fig. 3. The building structure is subjected to artificial horizontal earthquake acceleration at the base with main shock and aftershock in the direction of its width.

The external excitation input to that building is shown in Fig. 4. The main shock of earthquake starts at about 120 second. After the lapse of main shock, the ground accelerations returns to normal ambient conditions, and aftershock restarts at a time of 300 second and then it returns to the normal ambient conditions again.

Vibration data can be measured from 16 sensor nodes which are installed on each floor as shown in Fig. 3. Vibration data are sampled at every 0.02 second. Example plot of the vibration response is shown in Fig. 5. The detection index or threshold value corresponding to the normal operations and ambient vibrations of the building is taken as equal to 5.2×10^{-13} for the event-triggered monitoring simulation scheme.

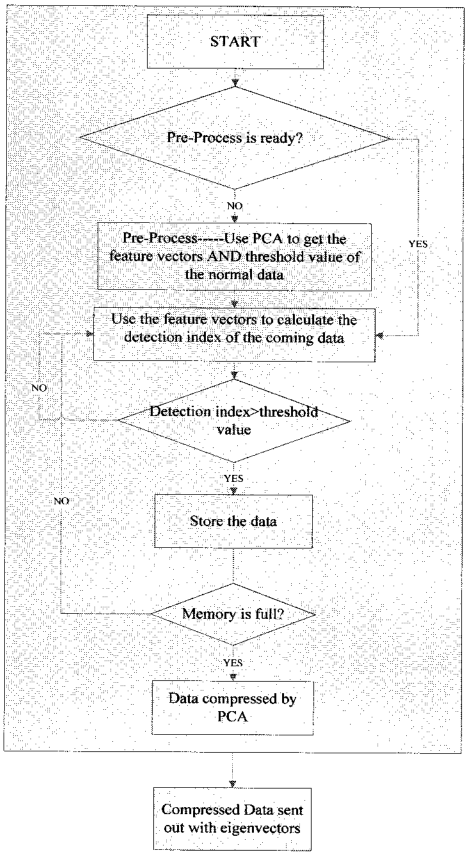

Fig. 2. Detailed process of event-triggered monitoring

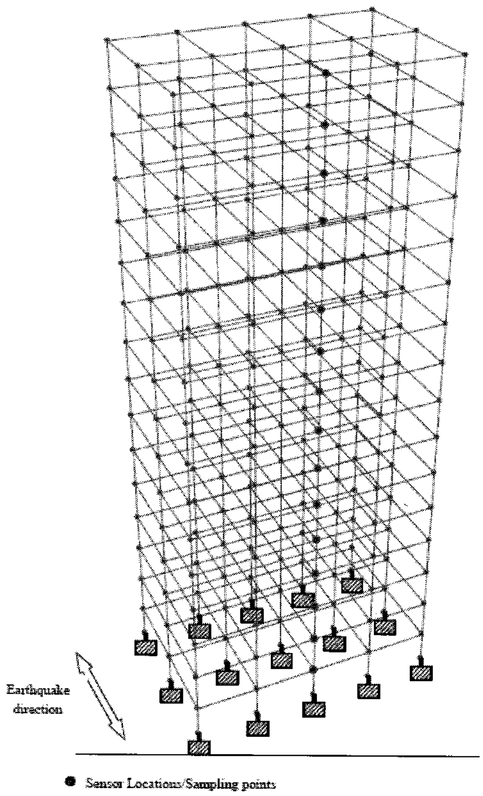

Fig. 3. Simulation model of 15-story building equipped with wireless sensor node at each floor

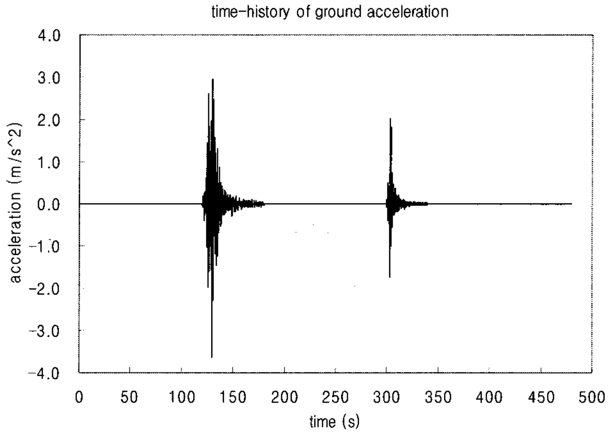

Fig. 4. Artificial external excitation input to the building

The threshold value of the SPE was initially evaluated for the first few periods of monitoring assumed to be under normal ambient vibration conditions that are considered to be not critical to the state of the structure.

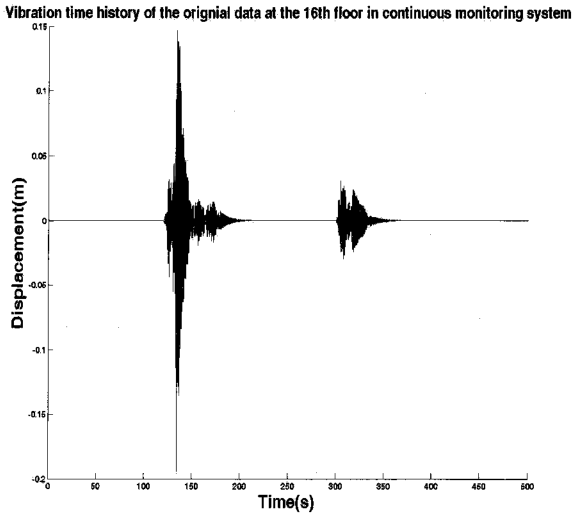

Fig. 5. Vibration data obtained on the 16th floor

As proposed in this study, an event-triggered type of wireless monitoring can be performed by utilizing the error signals from PCA. A plot of Squared Prediction Error (SPE) is shown in Fig. 6.

As can be seen from Fig. 6, SPE is important indicator to be used to decide when to start storing the coming data and when to stop storing it. Therefore, the stored vibration data which are coming from 16 sensor nodes are compressed by using PCA and the compressed data and its eigenvectors are transmitted to remote server. The original vibration data and its reconstructed data which can be viewed on server computer are shown in Figs. 7(a) and 7(b) respectively.

The reconstruction error between original data and reconstructed one is shown in Fig. 8. The details of the comparison have shown no significant differences between the observed responses as well as the peak displacements of the original measured data and the reconstructed sensor data with PCA.

The SPE signal corresponding to the aftershock event is shown in Fig. 9 and the original data and its reconstructed one are shown in Fig. 10. The reconstruction error between the original data and reconstructed one is also shown in Fig. 11 that shows no significant loss of information during the process of data compression.

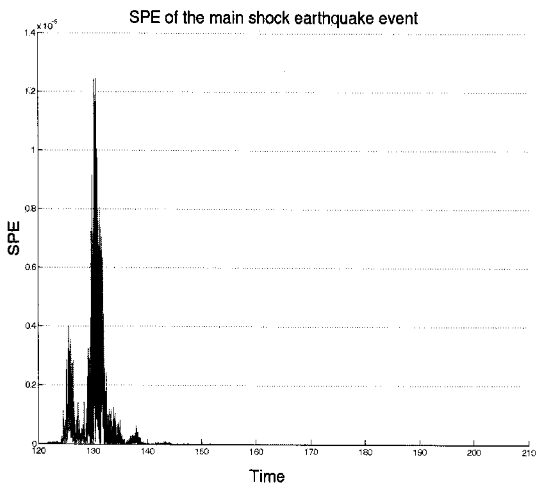

Fig. 6. Plot of SPE in event-triggered monitoring for the main shock earthquake event during the time of 120-200 seconds

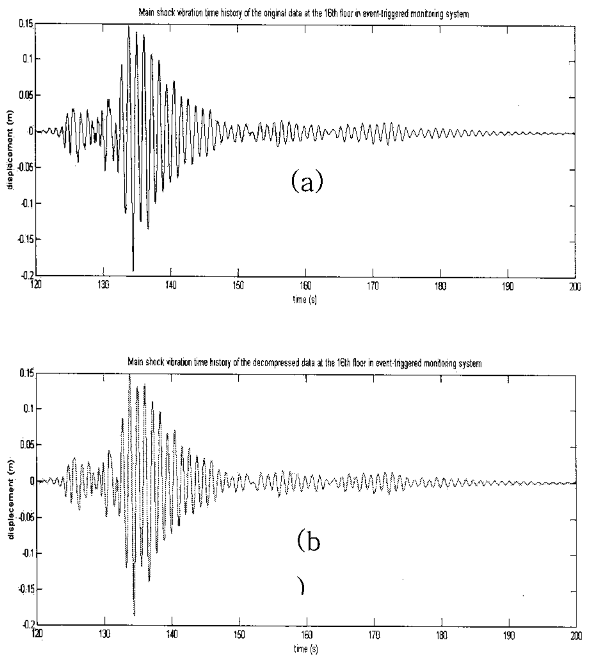

Fig.7.Vibration data at the 16th floor for the main shock earthquake event during the time of 120–200 seconds, (a) Original data, (b) reconstructed data on server computer

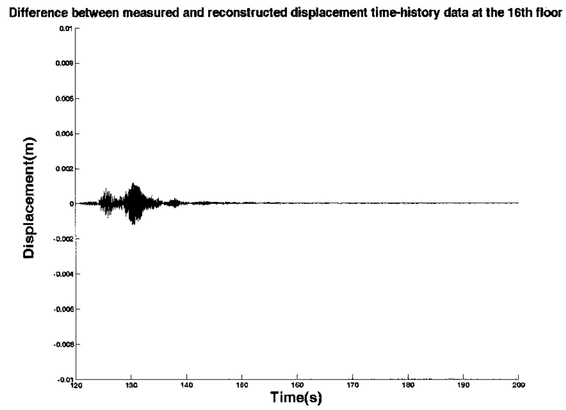

Fig. 8. Reconstruction error between original data and reconstructed one at the 16th floor during the main shock event at the time of 120–200 seconds

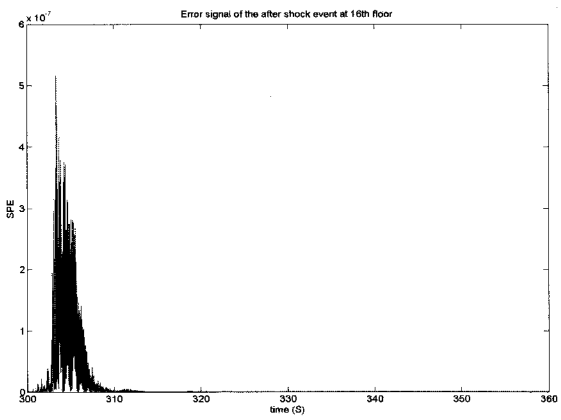

Fig.9. SPE Signal in an event-triggered monitoring for the aftershock event at the time of 300–360 seconds

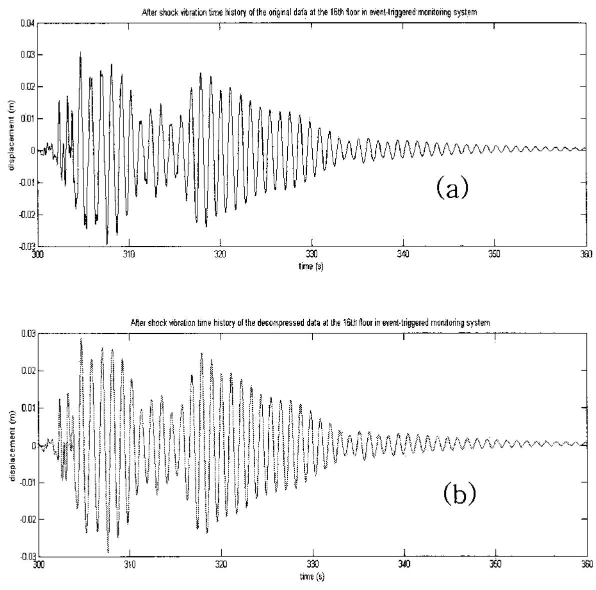

Fig.10. Vibration data at the 16th floor for the aftershock earthquake event at the time of 300–360 seconds, (a) Original data, (b) reconstructed data

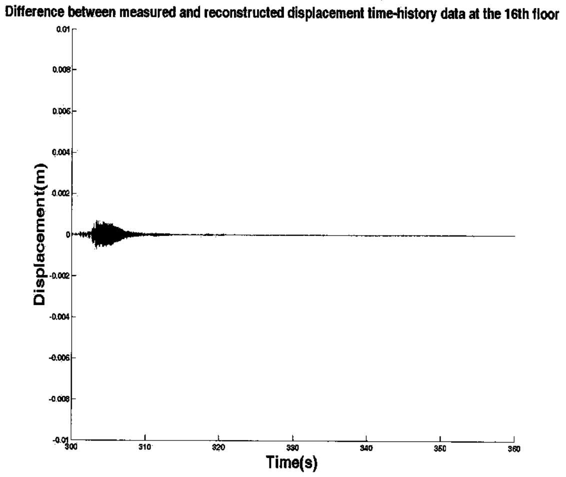

Fig. 11. Reconstruction error between original data and reconstructed one at the 16th floor during the aftershock event at the time of 300–360 seconds

5. Conclusions

A new type of structural monitoring system based on sensor network is proposed in this study. The proposed scheme utilizes SPE signal which is generated from PCA algorithms for efficient event detection and selective transmission of relevant data. The results of the simulation study shows the advantages and usefulness of the proposed method over the continuous type of structural monitoring system. Efficient data transmission without loss of information can be effectively achieved by employing event-triggered monitoring. These beneficial aspects of the proposed method will help improve the efficiency of large-sized wireless sensor networks.

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