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Structural damage detection considering sensor performance degradation and measurement noise effect

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ABSTRACT

In the real civil structures, material deterioration, overloading and environmental corrosion inevitably lead to sensor performance degradation or sensor fault. Sensor performance degradation or sensor fault usually introduce observable changes in the measured structural responses, which may be incorrectly interpreted as structural damage. This paper proposes a novel approach to quickly distinguish sensor fault from structural damage and locate the faulty or degraded sensors. Two steps are involved in this approach. In the first step, the root mean square of the generalized likelihood ratio test (GLRT) is used to detect and localize the structural damage or degraded sensors. In the second step, a new index is proposed used along with the statistical process control chart to distinguish sensor performance degradation from structural damage. The proposed index is the percentage of the extreme value of the largest principal component scores of the generalized likelihood ratio, which not only has excellent noise tolerance but also can distinguish sensor performance degradation from structural damage. The applicability and efficiency of the proposed approach are validated by numerical studies on a planar 11-element truss structure and experimental studies on a simply-supported steel beam in the laboratory. The results demonstrate that the proposed approach can locate the damage accurately when taking into account of sensor performance degradation and environmental noise in the measurements. The proposed index is able to accurately and quickly determine the source of the novelty in the responses.

1. Introduction

Structural health monitoring has been important for large-scale structures and at the same time challenging, particularly because of the progressive material degradation and significant noise effect. To ensure the safety and reliability of engineering structural operations, complex civil structures equipped with sensory systems are increasing due to the development of smart sensors and sensor network technology as well as a variety of applications exploiting sensor information. For example, as part of a sophisticated long-term monitoring system devised by the Hong Kong SAR Government Highways Department, Tsing Ma Bridge has been permanently instrumented with about 300 different types of sensors to monitor the structural health and safety conditions [1]. Since evaluating the operation or healthy states of structures is highly dependent on the measurement data recorded from installed structural health monitoring systems [2,3], it is very important to confirm whether the sensors work properly and output the reliable and accurate measurements. Otherwise the predictions from SHM systems might be questionable. However, in the real situations, deterioration in materials, overloading and environmental effect on civil engineering structures inevitably lead to sensor performance degradation or sensor fault [4,5]. Sensor performance degradation or sensor fault usually leads to changes in measured structural responses and vibration characteristics, which may be incorrectly interpreted as structural damage or condition anomaly. Under such circumstances, it is unreliable to detect structural damage using the measured data from sensors with degraded performance.

Numerous methods have been developed for vibration based structural damage detection in recent years [6]. Vibration responses from the sensors attached on the structures are used. In addition, various damage identification methods are based on signal processing and pattern recognition algorithms, such as Hilbert-Huang Transform [7], wavelet analysis [8], optimization

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algorithms and neural networks [9]. In most current methods, sensor performance degradation is not taken into consideration. Nevertheless, the performance of sensors is gradually degraded along with the development of material deterioration, overloading and environmental corrosion. Unfortunately, it seems that researchers have not paid a significant attention to consider the sensor performance degradation for an effective and accurate damage detection.

Fault detection and isolation methods, which have been widely studied in the areas of aerospace engineering [10] and industrial process monitoring, can be divided into four categories: hardware redundancy, analytical redundancy (physical model-based), knowledge-based and data-based methods [11]. However, hardware redundancy requires that the installed sensors in the network are more than the degree of the system, which is difficult for civil engineering. The analytical redundancy uses a mathematical model or physical model-building procedure of the structural system to isolate the faulty sensors. The process knowledge-based method is always time-consuming. However, data-based methods have become more popular recently since no accurate finite element model is required.

Data-based methods can involve Principal Component Analysis (PCA) [12,13], Independent Component Analysis (ICA) [14], Minimum Mean Square Estimation (MMSE) [15], factor analysis, and the parity space approach [16,17]. Therein, PCA-based statistical monitoring has been used for diagnosing sensor faults in many fields and it has great potential to play a part in SHM field for the following reasons: (1) the structural responses are measured as a multivariate process; (2) statistical correlations among the sensor measurements can be easily modeled by PCA; and (3) PCA is data-driven, which means it is very suitable for practical application because no structural model is required [18]. For example, Lee et al. [19] developed a faulty sensor identification method based on PCA. Harkat et al. [20] proposed a new index based on PCA for sensor fault identification and isolation. The results showed that the new index has an excellent performance compared with the squared prediction error (SPE). In structural health monitoring applications, for the sake of ensuring the accuracy of the sensor measurements, Kerschen et al. [13] developed a procedure base on PCA to detect, isolate the faulty sensors and recover the responses. Tharrault et al. [21] proposed a robust method to remove the effect of outliers on the PCA model for the detection and isolation of the faulty sensors. Sharifi et al. [22] presented a PCA-based sensor fault isolation method in the residual subspace rather than in the principal subspace, which is commonly used in industrial process monitoring data, specifically for smart structures. Subsequently, Sharifi and Langari [23] utilized Bayesian Belief Networks to find the conditional probabilities of faulty sensors' directional residuals and proposed an index for sensor fault detection. Huang et al. [18]. used Bayesian combination of weighted principal component analysis to theoretically quantify the fault sensitivity of each principal direction of PCA and diagnose sensor faults in structural monitoring systems.

Due to the fact that single or a few sensor responses could be estimated from the remaining sensor responses with sufficient training data from the sensor network by using MMSE [3,18], Kullaa [4] presented a method based on MMSE and PCA to distinguish structural damage from the sensor fault. In order to consider the severity of the faulty sensors, Kullaa [24] also extended the research to different sensor fault types, which were modeled, investigated and quantified by using the generalized likelihood ratio test. Moreover, Huang et al. [25] established a statistical hypothesis test model based on PCA and introduced two fault detection and isolation indices to identify the faulty sensor.

Among the abovementioned methods, PCA-based methods have been widely used in detecting and isolating degraded or faulty sensors. However, the traditional PCA-based indices may not be sensitive to detect the structural damage from the structural health monitoring data with the noise effect. This is because the environmental changes or structural damage in the measured structural responses are often of the same magnitude as those in the measured structural responses due to the sensor performance degradation. However, the purpose of structural health monitoring is to detect anomalies and/or damage at early stages.

This paper proposes a structural damage detection method taking in account of the sensor performance degradation and measurement noise effect, which is the extension of sensor fault detection method in our previous study [31]. More specifically, minimum mean square error estimation along with the generalized likelihood ratio test is firstly utilized to locate and detect the novelty. A new index, that is, the percentage of the extreme value of the largest principal component of the generalized likelihood ratio, is developed based on the statistical process control chart to distinguish sensor performance degradation from structural damage. Compared with former PCA based index [31], the novel index can distinguish fault sensor and avoid pattern recognition.

This paper is organized as follows: a novel two-stage damage detection method is proposed in Section 2; afterwards, a numerical simulation of 11-elment truss structure and an experiment of a steel beam in laboratory are performed in Sections 3 and 4, respectively; finally, Section 5 gives concluding remarks.

2. Damage detection considering sensor performance degradation and measurement noise effect

This section proposes a two-step structural damage detection approach by using the generalized likelihood ratio test (GLRT) and statistical process control (SPC) to identify structural damage taking into account of sensor performance degradation and measurement noise effect. The flow chart of the proposed approach is shown in Fig. 1. A two-step structural damage detection strategy is proposed. In the first step, the response from each sensor is examined and the root mean square (RMS) values of GLRT are utilized to detect the abnormal signal. In this study, the maximum RMS value may correspond to the possible novelty in the sensor responses. In the second step, a new index is proposed to perform a statistical analysis using SPC chart. This index can not only distinguish sensor performance degradation from structural damage but also decrease the impact of environmental noise effect. The new index is defined as the percentage of the extreme value of the largest principal component of generalized likelihood ratio. It shall be noticed that when the new index is out of the control limits in statistical process control chart, the novelty comes from sensor degradation; otherwise, the novelty from structural damage. The detailed theoretical background and procedures will be presented in the next sections.

2.1. The first-step: novelty location

In the first step, RMS values of GLRT are employed to distinguish the possible sensor performance degradation or structural damage.

2.1.1. Minimum mean square error (MMSE) estimator

As commonly described, the output of a sensor network follows Gaussian distribution [4], which can be described by using a mean vector $\boldsymbol{\mu}$ and a covariance matrix $\sum$. This can be expressed as

$$p(\boldsymbol{x}) = |2\pi\Sigma|^{-1/2}\exp\left[-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu})^T\Sigma^{-1}(\boldsymbol{x}-\boldsymbol{\mu})\right] \tag{1}$$

where x is the measured data sample of accelerations.