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Sensor validation using minimum mean square error estimation

Jyrki Kullaa [a,b,*]

[a] Department of Applied Mechanics, Helsinki University of Technology, Finland
[b] Department of Mechanical and Production Engineering, Helsinki Metropolia University of Applied Sciences, P.O. Box 4021, FIN-00079 Metropolia, Finland

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ABSTRACT

Sensor fault can be detected and corrected in a multichannel measurement system with enough redundancy using solely the measurement data. A single or multiple sensors can be estimated from the remaining sensors if training data from the functioning sensor network are available. The method is based on the minimum mean square error (MMSE) estimation, which is applied to the time history data, e.g. accelerations. The faulty sensor can be identified and replaced with the estimated sensor. Both spatial and temporal correlation of the sensors can be utilized. Using the temporal correlation is justified if the number of active structural modes is larger than the number of sensors. The disadvantages of the temporal model are discussed. Experimental multichannel vibration measurements are used to verify the proposed method. Different, and also simultaneous, sensor faults are studied. The effects of environmental variability and structural damage are discussed.

1. Introduction

Structures equipped with sensors are becoming common due to the development of the sensor and sensor network technology as well as different applications exploiting sensor information. For example, vibration-based structural health monitoring is heavily based on the measurement data recorded during a long period. It is therefore most important that the sensors are working properly and possible sensor faults are detected in order to maintain the reliability of the system. Otherwise a sensor fault can be misinterpreted as a structural damage. Monitoring systems typically include several sensors at different locations of the structure in order to extract features for damage detection or damage localization. Such sensor network constitutes a redundant system, which can be used to detect sensor malfunction or failure, identify, and even correct the faulty sensor. These topics are discussed in this study.

Dunia et al. [1] studied detection, isolation, and reconstruction of a faulty sensor using principal component analysis (PCA). They reconstructed each sensor in turn using the remaining sensors, and calculated a sensor validity index from residuals before and after reconstruction for fault detection and isolation. They proposed two approaches to reconstruct a single sensor, an iterative method and optimization, both resulting in the same closed-form solution. Different types of fault, bias, complete failure, drifting, and precision degradation were studied. Different residuals were investigated. They proposed a sensor validity index (SVI) to identify the faulty sensor by replacing one sensor in turn with the estimated sensor. The minimum SVI was found in the case where the faulty sensor was replaced with the estimated one. Dunia and

* Corresponding author at: Department of Mechanical and Production Engineering, Helsinki Metropolia University of Applied Sciences, P.O. Box 4021, FIN-00079 Metropolia, Finland, Tel.: +358 207836176; fax: +358 207836102.
E-mail address: jyrki.kullaa@metropolia.fi

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Qin [2] also derived conditions for fault detectability, reconstructability, and identifiability. Both sensor and process faults could be identified, but the fault direction must be known, which is easy for a sensor fault, but difficult for process faults.

Kerschen et al. [3,4] also applied PCA to sensor validation and used the angle between the principal subspaces as a feature for fault detection. The principal component analysis was made separately for each time record. They also derived a closed-form equation to estimate a single sensor. The faulty sensor was identified by removing one sensor in turn. The faulty sensor was the removed sensor in the case with the minimum angle.

Friswell and Inman [5,6] introduced a sensor validation method based on the modal model of the structure. The advantage is that the sensors are not assumed to be functioning initially but instead a modal model has to be available. Two approaches were studied, modal filtering and PCA. They concluded that the modal filtering approach performs better if an accurate modal model is available. They also found that a multiplicative sensor fault is more difficult to locate than an additive fault.

Abdelghani and Friswell [7,8] studied model-based methods to validate sensors with additive or multiplicative faults. Two residual generation techniques were studied with an additive fault, the parity space and the modal filtering approaches. For the multiplicative fault, they introduced a correlation index to isolate the faulty sensor. The index was computed from proposed new residuals.

Hernandez-Garcia and Masri [9] compared PCA, independent component analysis (ICA), and modified ICA (MICA) for sensor fault detection. They used two features for fault detection: the Hotelling's T^2 statistic and the squared prediction error (SPE). They concluded using a numerical model that the detection performance of ICA and MICA was higher than that of PCA.

A disadvantage of PCA is that the number of principal components must be determined, which is not always straightforward with noisy data. It has also been reported that the estimation of several variables simultaneously is complex. This is needed if more than one sensor is faulty or if temporal correlation is also applied.

Kullaa [10] introduced factor analysis for sensor validation and compared it with PCA. Similar to PCA, factor analysis also has one parameter, the number of factors, which has to be chosen. However, the sensitivity to the parameter was seen to be lower than in PCA. Also, a closed-form solution to reconstruct several sensors using the remaining sensors was derived.

Kullaa [11] introduced the minimum mean square error (MMSE) estimation to sensor validation. It works directly in the data space without a need to determine any model parameters, but with a cost of a slower performance. Also, a spatiotemporal extension was introduced [12], which can be applied if the number of sensors is lower than the number of active modes in the structure. The estimation error was also derived but not applied in the study. The faulty sensor was identified by removing one sensor in turn and performing MMSE estimation to the remaining sensors. The faulty sensor was the missing sensor in the analysis with the lowest mean-square residual compared to that of the training data. The main disadvantage is that the analysis has to be made for each sensor resulting in a slow performance.

In this paper, a considerably faster algorithm for sensor validation is derived based on the MMSE estimation. The performance of both the sensor estimation and faulty sensor identification are increased. Also, the estimation error is utilized in the faulty sensor identification, which results in a higher reliability compared to the previously proposed method [11].

In most of the aforementioned studies it was assumed that the number of sensors is higher than the number of excited modes. If the number of active modes is larger than the number of sensors, there is a lack of redundancy between sensors. The time histories could then be filtered to a limited bandwidth. Another solution is to use temporal correlation together with spatial correlation. Spatial correlation contains information between the sensors at the same time instant (a snapshot of the structural motion), whereas temporal correlation contains frequency information. Bearing this in mind, it would be advantageous to use spatial correlation only to distinguish between structural damage and sensor fault. Natural frequencies have been observed to be more sensitive to structural damage or environmental variations than the mode shapes. These effects are also studied in this paper.

The linear MMSE estimator model is derived in the next section followed by the spatiotemporal correlation model. Algorithms for sensor fault detection, identification, and correction are proposed. The method uses solely the measurement data, no numerical model of the structure is needed. The model is then applied to an experimental study of a wooden bridge. It is first assumed that one sensor only is faulty but later simultaneous sensor faults are also investigated. Different fault types, bias, drifting, precision degradation, and gain are studied. Additive and multiplicative faults result in a change of different statistics. Also, the effects of the environment and minor damage are studied. The spatiotemporal correlation model is compared to the purely spatial correlation model. Finally, conclusions and practical suggestions from the research are given.

2. Minimum mean square error (MMSE) estimator

Sensor validation is approached by estimating one or more sensors using the remaining ones. The likelihood ratio test is then applied to detect sensor fault. It is assumed that training data have been acquired from the sensor network, in which all sensors are functioning. It is also assumed that the number of active structural modes is less than the number of sensors. This is a necessary condition for enough redundancy. Later, this condition can be relaxed if temporal correlation is also taken into account.

In multivariable measurements with enough redundancy, a subset of observation can be estimated using the remaining variables. Each observation is divided into observed variables $\mathbf{v}$ and missing variables $\mathbf{u}$:

$$\mathbf{x} = \begin{Bmatrix} \mathbf{u} \\ \mathbf{v} \end{Bmatrix} \tag{1}$$