Applying Sensitivity Analysis in Structure Damage Identification

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Abstract. Structure health monitoring aims to detect the nature of structure damage by using a network of sensors, whose sensor signals are highly correlated and mixed with noise, it is difficult to identify direct relationship between sensors and abnormal structure characteristics. In this study, we apply sensor sensitivity analysis on a structure damage identifier, which integrates independent component analysis (ICA) and support vector machine (SVM) together. The approach is evaluated on a benchmark data from University of British Columbia. Experimental results show sensitivity analysis not only helps domain experts understand the mapping from different location and type of sensors to a damage class, but also significantly reduce noise and improve the accuracy of different level damages identification.

1 Introduction

Structural stiffness decreases due to aging, damages, and other harmful effects. These adverse changes lead to abnormal dynamic characteristics in natural frequencies and mode shapes. By instrumenting structures with a network of sensors, structural health monitoring (SHM) aims to provide reliable and economical approaches to detect the nature of structure damage in an early stage so as to prevent catastrophic failures[1,2]. The technology of machine learning has been used, such as independent component analysis (ICA) or principal component analysis (PCA) for feature extraction, artificial neural networks (ANN) or support vector machines (SVM) for classification. However, the complicated data transformation and classification make it difficult to identify direct relationship between sensors and abnormal structure characteristics. Structure engineers are keen to explore the relationship because different type and location sensors have empirically been proved to provide varied quality information.

In this paper, firstly ICA with SVM is combined together to construct a structure damage classifier. Next, the classifier is regarded as a black box and apply ICA-SVM based first-order sensitivity analysis to select most important sensors. Our experiments, based on the benchmark data from University of British Columbia, showed sensitivity analysis can clearly reveal the relationship between selected sensors and

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specific damages, and the ICA-SVM classifier significantly improves the identification accuracy with the most sensitive signals.

2 Methodology

2.1 Architecture of Structure Damage Classifier on Sensitive Sensors

The architecture of sensitive information prediction based on ICA and classifiers SVM is shown in Fig.1, where Fast-ICA algorithm is used with a non-quadratic function g(y) = tanh (a1×y) to measure nongaussianity, and linear kernel function is used in SVM [3].

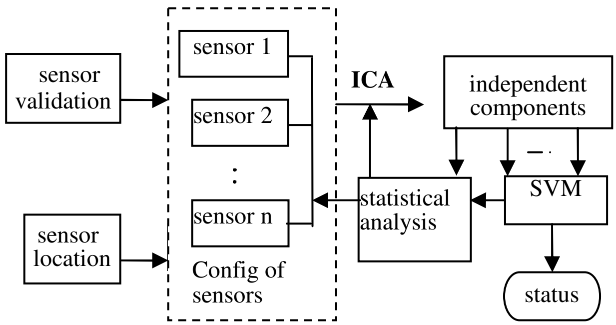

Fig. 1. Architecture of sensitive information prediction

2.2 ICA-SVM Based Sensitivity Analysis

By sensitivity analysis, the classifier is regarded as an ICA-SVM black box, whose inputs are sensor signals x_1, x_2, …, x_h and output is status label Y. We assume each signal x_i (i=1,2,…,h) observers normal distribution with $N(\overline{x_i}, \sigma_i)$. By perturbing a sensor signal with a small value Δx_i, we explore how much difference a new predictor Y_i will make, comparing with the predictor Y_{full} constructed by full set of original sensor signals. Thereby, the normalized stimulation sensitivity $S_i = \frac{\Delta Y_i / \sigma_{Y_i}}{\Delta x_i / \sigma_i} = \frac{\sigma_i (Y_i - Y_{full})}{\sigma_{Y_i} \Delta x_i}$, where σ_{Y_i} is the standard derivation of predictor Y_i. Given all sensor signals have the same standard derivation, $\sigma_i = \sigma_j$, $\sigma_{Y_i} = \sigma_{Y_i}$ (here i,j=1,2,…, h and $i \neq j$), S_i is simplified as the first-order derivative $\frac{(Y_i - Y_{full})}{\Delta x_i}$. Sorting the S_i, we will rank the sensors signals by their sensitivity. The top features play the most important roles in the damage detection. The detailed algorithm is listed in [4].

3 Experiments

A popular benchmark to testify the classification accuracies is used, which was set up by the IASC-ASCE SHM task Group at University of British Columbia. The structure is a 4-story, 2-bay by 2-bay steel-frame scale-model structure, which has a 2.5 m × 2.5m plane and is 3.6m tall[5]. In our experiments, seven data sets in the ambient data was served, where C01 is an undamage dataset, C02-C07 are different type of damaged datasets. There are 15 attributes in each dataset. They correspond to the signals from 15 sensors located in this steel-frame, and the 16 attribute is noise attribute.

3.1 Experimental Results

(1) Sensitive sensor list
For each undamaged or damaged dataset, 6000 samples are randomly chosen. According to sensitive information algorithm, we obtain a sorted attribute list shown in Table 1. The bold attributes denotes they have been selected into sensitive sensor list SL. The table also helps domain experts to explore different location and type of sensors to a specific damage class.

Table 1. Sorted attributes list

Data	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th	14th	15th
C01	**4**	**12**	**6**	**11**	**2**	**1**	**15**	13	3	14	8	5	9	7	10
C02	**11**	**4**	**13**	**5**	**15**	**6**	**1**	2	3	8	7	12	14	10	9
C03	**15**	**6**	**3**	**2**	**9**	**4**	**11**	12	7	1	13	5	14	8	10
C04	**15**	**9**	**10**	**13**	**6**	**14**	**12**	2	1	7	11	3	5	4	8
C05	**12**	**10**	**11**	**1**	**13**	**3**	**4**	2	8	5	15	14	9	6	7
C06	**7**	**10**	**3**	**2**	**9**	**12**	**1**	14	15	4	11	6	5	13	8
C07	**8**	**15**	**14**	**7**	**12**	**2**	**4**	6	5	13	3	1	10	11	9

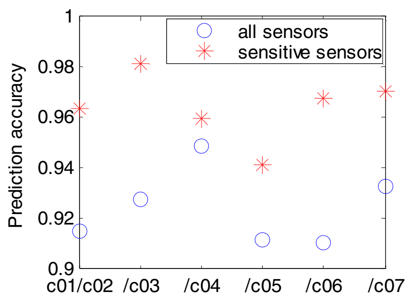

Fig. 2. Two damage identification

For all seven data sets in Table 1, we counted the total occurring frequency for each selected sensitive attribute, and get 7 attributes 4,12,15,1,2,6,11 occurring more than 3 times in all datasets.

(2) Identification of two kinds of damage level
For comparing the classification on accuracy by using all signals or using the most sensitive 7 signals, two damage levels experiment is done. 70% of C01 work as for training, the remaining 30% of C01 as test; and the same number of samples from another damaged dataset in C02-C07 for test, the result is shown in Fig.2, which shows sensitive sensors significantly improve the prediction accuracy.

(3) Identification of multi-damage level
Further comparing the classification on accuracy by using all signals or using the most sensitive 7 signals, multi-damage levels experiments are done.For multi-damage level experiment, C01 is treated as undamage data, its output is ‘1’ ; C02 is regarded

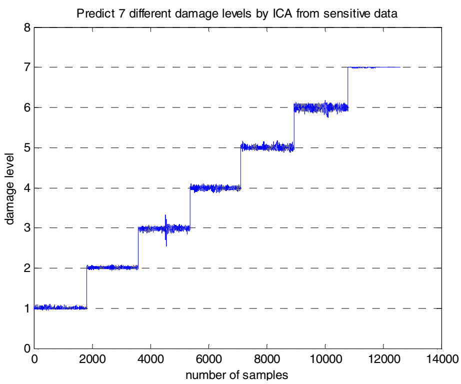

Fig. 3. Prediction with sensitive sensors

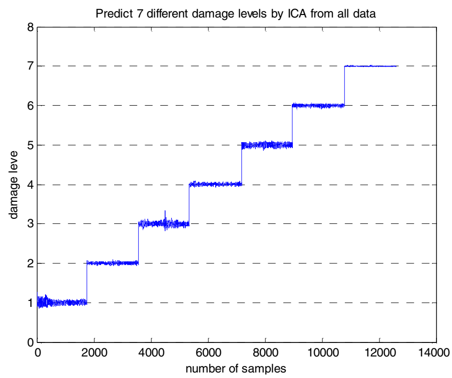

Fig. 4. Prediction with all sensors

as damage data whose output is '2', and so on. 70% of C01-C07 are training data, the rest 30% of C01-C07 are test data, predict the damage value. The results is shown in Fig.3 and Fig.4.

The above experiments show that the sensitive sensors can get an accuracy prediction for different damage levels .Compared with used all sensors, the number for sensitive sensors is reduced nearly half of all sensors, but it can performs damage identification well. They show the validity of the architecture in Fig.1.

4 Conclusions

In this paper, sensitivity analysis is applied in a structure damage classifier, whose architecture combines ICA with SVM, and it is evaluated by the benchmark data from University of British Columbia. The damage detection accuracy using sensitive attributes is significantly better than those obtained by using full sensor signals in two damage level identification; it can perform well for multi-damage level identification.

References

[1] S.W. Doebling, C.R. Farrar, (et): A Summary Review of Vibration-Based Damage Identification Methods, The Shock and Vibration Digest, 30 (2), (1998) 91-105

[2] T. Pothisiri, K. D. Hjelmstad: Structural Damage Detection and Assessment from Modal Response, J. of Engineering Mechanics, 129 (2) , (2003)135-145

[3] H. Song, L. Zhong, (et): Structural Damage Detection by Integrating Independent Component Analysis and Support Vector Machine. ADMA, Springer LNAI3584, (2005) 670-677

[4] B. Han, L. Kang, (et): Improving Structrue Damage Identification by Using ICA-ANN Based Sensitivity Analysis. ICIC 2006, Accepted.

[5] http://www.bc.cityu.edu.hk/asce.shm