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Structural damage identification via a combination of blind feature extraction and sparse representation classification

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ABSTRACT

This paper addresses two problems in structural damage identification: locating damage and assessing damage severity, which are incorporated into the classification framework based on the theory of sparse representation (SR) and compressed sensing (CS). The sparsity nature implied in the classification problem itself is exploited, establishing a sparse representation framework for damage identification. Specifically, the proposed method consists of two steps: feature extraction and classification. In the feature extraction step, the modal features of both the test structure and the reference structure model are first blindly extracted by the unsupervised complexity pursuit (CP) algorithm. Then in the classification step, expressing the test modal feature as a linear combination of the bases of the over-complete reference feature dictionary—constructed by concatenating all modal features of all candidate damage classes—builds a highly underdetermined linear system of equations with an underlying sparse representation, which can be correctly recovered by ℓ_1-minimization; the non-zero entry in the recovered sparse representation directly assigns the damage class which the test structure (feature) belongs to. The two-step CP–SR damage identification method alleviates the training process required by traditional pattern recognition based methods. In addition, the reference feature dictionary can be of small size by formulating the issues of locating damage and assessing damage extent as a two-stage procedure and by taking advantage of the robustness of the SR framework. Numerical simulations and experimental study are conducted to verify the developed CP–SR method. The problems of identifying multiple damage, using limited sensors and partial features, and the performance under heavy noise and random excitation are investigated, and promising results are obtained.

1. Introduction

The damage identification problem in structural health monitoring (SHM) commonly includes four levels [1]: (1) detecting the presence of damage; (2) locating damage; (3) assessing damage severity; (4) predicting the structural remaining service life. Vibration-based damage identification techniques [2] have been extensively studied in the literatures [3]. In the earlier years, much attention was focused on those methods based on the change of structural modal parameters as damage signature; specifically, the frequency tends to reflect global damage information while the modeshape may additionally provide spatial information of damage. However, researchers have pointed out that modal information alone is

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not sensitive to local damage and that its capability as direct damage indicators is easily influenced by noise. Nevertheless, researches do converge to support the conclusion that structural damage information is hidden in modal features, which need to be further processed for successful damage identification.

Novel signal processing techniques, on the other hand, have been successfully applied in the recent years to detect and locate structural damage, such as wavelet transform [4–6], Hilbert–Huang transform [7,8], time–frequency analysis [9,10], fractal dimension [11,12], cyclostationarity [13], and blind source separation [14–16]. The signal-based methods are typically non-parametric and enjoy efficient implementation; they are mostly limited up to the level 2, however.

With a structural model (e.g., a finite element model) available as reference information, it is possible to develop damage identification methods that can address even the problem of level 3 [3], that is, the quantification of damage severity. Some researchers used the model updating method [17,18] to address this problem, by comparing the undamaged (reference) and candidate (test) model (physical or modal) matrices [3]. These methods are essentially parametric; as such, they are prone to model error.

More recently, the damage identification problem including that of level 3 has been treated as a pattern recognition issue [14,19–27]. The classification-based methods involve three steps: *feature extraction*, *training*, and *classification*. For damage identification, the extracted features from various predefined or reference damage classes, including different damage locations and damage extents, are used as inputs to train the classifiers, which can then identify the damage class of the test feature representing the current state of the structure. Successful examples include those based on artificial neural networks (ANNs) [14,20], support vector machines (SVMs) [22–25], nearest neighbor [26], and Markov observers [27].

Several factors, however, could influence the performance of these classification-based damage identification methods that are mostly dependent on the training process of the classifiers. In the ANN-based methods, for example, the number of input and hidden nodes in the network could affect its accuracy [14,20], and the global convergence of the algorithm is not guaranteed [19]. Compared to ANN, the multi-class SVM-based methods have advantages when the sample numbers are small [21,23]; nevertheless, their success depends on the choice of the algorithm parameters, i.e., the kernel function selection and its associated parameters [21,22,24]. Although optimal choice may be obtained through trial and error or optimization algorithms, and such an approach increases computational burden and needs the skill of an experienced practitioner; hence is not preferable in some situations, e.g., online monitoring.

Attempting to address the aforementioned concerns, this paper proposes a new algorithm in the classification framework for both locating and assessing structural damage, using the recent theory from blind source separation (BSS) [28] and sparse representation (SR) [29] along with compressed sensing (CS) [30,31]. The proposed damage identification method consists of two steps: feature extraction and classification.

Specifically, in the feature extraction step, a BSS method termed complexity pursuit (CP) [32] is used to extract the modal features of the structure. As an unsupervised learning algorithm, BSS is able to recover the hidden sources using only the measured mixture signals. Recently, two BSS techniques—independent component analysis (ICA) [33] and second order blind identification (SOBI) [34]—have been studied extensively in structural dynamics and found to be efficient in output-only modal identification [35–42]. However, it is to be noted that ICA is only suitable for lightly-damped structures [36,41], while SOBI overcomes this difficulty, yet has difficulty in handling cases with close modes and non-stationary vibrations [39,40]. Time–frequency ICA [41] and modified SOBI methods [39,40] have been proposed to address these drawbacks; especially, the extended SOBI method recently proposed in Ref. [42] has tackled quite a few earlier limitations in SOBI based methods.

Another BSS technique, CP, recently explored by the authors [43], has been found to be a useful alternative to efficiently perform output-only system identification of many structures with highly-damped, closely-spaced, and non-proportionally damped modes requiring limited parameter adjustments. In the first step of the proposed method, CP serves to blindly extract the structural modal features, which are subsequently used by the classification framework for damage identification; its performance is also compared with SOBI.

In the following classification step for both locating damage and identifying damage extent, the sparsity nature of the classification itself is exploited. An SR framework is developed based on the theory of SR and CS [29–31], due to their recent success on sparse MRI [44], robust SR face recognition [45], and more lately on SHM [46–49]. The key idea is that the damage class of the test structure naturally belongs to only one unique class of the predefined reference feature space: (1) an over-complete reference feature dictionary is built by concatenating all the modal features of all candidate damage classes; (2) the test modal feature is most sparsely represented as a linear combination of the bases of this reference dictionary, activating only the relevant feature in the same damage class. This establishes a highly underdetermined linear system of equations with an underlying sparse representation that directly dictates the damage class of the test structure. The theory of SR and CS enables one to find the correct sparse solution of such a highly underdetermined linear system of equations using the efficient ℓ_1-minimization technique, leading to the test structure's class of damage location and damage severity.

Numerical simulations and experimental study are conducted to verify the proposed CP–SR method. Results show that it can accurately and efficiently identify the damage locations and damage extents. In addition, several problems of identifying multiple damage, using limited sensors and partial features, and in the presence of heavy noise and random excitation are also presented.

The remainder of this paper is organized as follows. Section 2 introduces the theory of BSS and CP for the feature extraction step, and Section 3 presents the SR classification framework for damage identification. Section 4 summarizes the