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Machine learning algorithms for damage detection: Kernel-based approaches

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ABSTRACT

This paper presents four kernel-based algorithms for damage detection under varying operational and environmental conditions, namely based on one-class support vector machine, support vector data description, kernel principal component analysis and greedy kernel principal component analysis. Acceleration time-series from an array of accelerometers were obtained from a laboratory structure and used for performance comparison. The main contribution of this study is the applicability of the proposed algorithms for damage detection as well as the comparison of the classification performance between these algorithms and other four ones already considered as reliable approaches in the literature. All proposed algorithms revealed to have better classification performance than the previous ones.

1. Introduction

Civil structures such as buildings, roads, railways, bridges, tunnels and dams are present in every society, regardless of culture, geographical location or economical development. The safest and most durable structures are those that are well managed and maintained. Health monitoring plays an important role in management activities [1]. The massive data obtained from monitoring must be transformed in meaningful information to support the planning and designing maintenance activities, increase the safety, verify hypotheses, reduce uncertainty and to widen the knowledge and insight concerning the monitored structure.

Structural health monitoring (SHM) is certainly one of the most powerful tools for civil infrastructure management. The SHM process consists of permanent, continuous, periodic or periodically continuous acquisition of parameters by a sensor network, feature extraction and statistical modeling for feature classification to detect possible structural damages and to support the decision making [2,3]. Damage is traditionally defined as changes in the material and/or geometric properties of the structures, including variations in the boundary conditions and system connectivity, which adversely affect the system's current or future performance. In contrast, normal condition refers to data acquired under different operational and environmental variability when the structure is known to be undamaged [4,5].

In the feature extraction phase is imperative to derive damage-sensitive features correlated with the severity of damage present in monitored structures, minimizing false judgements in the classification phase. Nevertheless, in real-world SHM applications, operational and environmental effects can camouflage damage-related changes in the features as well as alter

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the correlation between the magnitude of the features and the damage level. Commonly, the more sensitive a feature is to damage, the more sensitive it is to changing in the operational and environmental conditions (e.g., temperature and wind speed). To overcome this impact, robust feature extraction procedures are usually required [6–8].

Statistical modeling for feature classification phase is concerned with the implementation of machine learning algorithms that analyze the distributions of the extracted features and generate a data model in an effort to determine the structural health of the system. The algorithms used in statistical modeling usually fall into the outlier detection category, i.e., unsupervised learning is applied when training data are only available from the normal condition of the structure [9,10]. The data normalization procedure is normally present in the data acquisition, feature extraction and statistical modeling phases of the SHM process. Herein, data normalization includes a wide range of steps for removing the effect of operational and environmental variations on the extracted features [11].

Kernel-based machine learning algorithms have been widely applied to detect damage in SHM applications [12–16]. These algorithms, mostly based on support vector machines (SVMs), have revealed high sensitivity and accuracy in the damage classification. Mita and Hagiwara proposed a method using the supervised SVM to detect local damages in a building structure with limited number of sensors [17]. This method has been extended in several studies. For instance, a hybrid technique (wavelet SVM) may be considered, where damage-sensitive features are extracted through the wavelet energy spectrum and classified using the SVM [18]. In turn, a combined methodology between symbolic data analysis and classification techniques (e.g., SVM) is developed for damage assessment [19]. And, finally, an approach for detecting damage on shear structures using the SVM and the first three natural frequencies of the translational modes is assumed [20]. However, these approaches have not been implemented to remove the operational and environmental effects aggregated in extracted features; rather, they have been used to classify directly the extracted features in a supervised way, i.e., when data from the undamaged and damaged conditions are available.

However, for most civil engineering infrastructure where SHM systems are applied, the unsupervised learning algorithms are often required because only data from the undamaged condition are available [21,22]. Therefore, in this paper, an autoregressive (AR) model is used to extract damage-sensitive features upon time-series measured from an array of accelerometers, when the structure operates in different structural state conditions. Then, four unsupervised kernel-based machine learning algorithms are adapted for data normalization and damage detection. Firstly, they model the effects of the operational and environmental variability on the extracted features. Secondly, each algorithm produces a scalar output as a damage indicator (DI), which should be nearly invariant when features are extracted from the normal condition. Finally, DIs from the feature vectors of the test data are classified through a threshold defined based on the 95 percent cut-off value over the training data. The implemented algorithms are based on one-class support vector machine (one-class SVM), support vector data description (SVDD), kernel principal component analysis (KPCA) and greedy KPCA (GKPCA).

The main contribution of this study is the applicability of the proposed kernel-based algorithms for damage detection as well as the comparison of the classification performance, between these kernel-based algorithms and other reliable algorithms described in the literature [9,23–26], such as the auto-associative neural network (AANN) [11,27], factor analysis (FA) [28], Mahalanobis squared distance (MSD) [29], and singular value decomposition (SVD) [30], on standard data sets from a laboratory three-story frame aluminum structure. The performance is evaluated through receiver operating characteristic (ROC) curves, which are a means of determining performance on the basis of Type I/Type II error trade-offs. In SHM, in the context of damage detection, a Type I error is a false-positive indication of damage and a Type II error is a false-negative indication of damage. Besides, other contributions attested by the authors are the following: the first-time adaptation of the KPCA and GKPCA algorithms for damage detection in the SHM field; and the combination between one-class SVM/SVDD and MSD for data normalization purposes in the SHM field, particularly in the statistical modeling for feature classification phase.

This paper is organized as follows. Section 2 gives an explanation about the AR model for feature extraction, a brief background about the supervised SVM with the kernel trick for efficient optimization and the methodology of the four kernel-based machine learning algorithms for feature classification. A description of the test bed structure, the simulated operational and environmental variability, and a summary of the data sets is provided in Section 3. In Section 4, a comparative study between kernel-based algorithms and alternative approaches is carried out using features extracted from time-series data sets measured with accelerometers deployed on the test bed structure. Finally, Section 5 highlights a summary and discussion of the implementation and analysis carried out in this paper.

2. Feature extraction and kernel-based machine learning algorithms

The complete methodology applied in this study is depicted in Fig. 1. Basically, AR models are fitted to time series from an array of accelerometers when the structure is in different structural state conditions and their parameters are used as damage-sensitive features. Then, a training matrix, $\mathbf{X}$, is composed of undamaged state conditions and a test matrix is composed of undamaged and damaged state conditions. Next, an unsupervised machine learning algorithm is trained and its parameters are adjusted using feature vectors from the training matrix only. In the test phase, the machine learning algorithm will transform each input feature vector from the test matrix, $\mathbf{Z}$, into a global DI; the DIs should be nearly invariant for feature vectors extracted from the normal condition, assuming that the test data have been obtained from operational and environmental conditions represented in the training data. Finally, the classification is performed using one-sided