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An online input force time history reconstruction algorithm using dynamic principal component analysis

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ABSTRACT

The knowledge of dynamic loads acting on a structure is always required for many practical engineering problems, such as structural strength analysis, health monitoring and fault diagnosis, and vibration isolation. In this paper, we present an online input force time history reconstruction algorithm using Dynamic Principal Component Analysis (DPCA) from the acceleration time history response measurements using moving windows. We also present an optimal sensor placement algorithm to place limited sensors at dynamically sensitive spatial locations. The major advantage of the proposed input force identification algorithm is that it does not require finite element idealization of structure unlike the earlier formulations and therefore free from physical modelling errors. We have considered three numerical examples to validate the accuracy of the proposed DPCA based method. Effects of measurement noise, multiple force identification, different kinds of loading, incomplete measurements, and high noise levels are investigated in detail. Parametric studies have been carried out to arrive at optimal window size and also the percentage of window overlap. Studies presented in this paper clearly establish the merits of the proposed algorithm for online load identification.

1. Introduction

Precise identification of input force excitation has greater significance in many structural dynamic problems, such as structural dynamic design, response reconstruction, condition assessment and health monitoring. Unfortunately, in many practical applications, it is difficult to directly measure input excitation. In some situations, if force gauges are inserted into force transfer path to measure the excitations, it is difficult to obtain the accurate forces since the existence of the force gauges may alter the system properties. And also, an impact force with large magnitude for a short time period is extremely difficult to measure [1]. However, it is rather easier to measure acceleration time history responses. Since we know the time history responses, we can reconstruct the input force time history by inverse formulations.

These inverse techniques for input force reconstruction can be formulated either using frequency domain [1–6] or time domain [7–12] methods. The input force spectra identification in frequency domain approaches is popularly realized by establishing the relationship between input force and response spectra using frequency response functions. On the other hand, time-domain methods, based on the kinetic equation, are formulated in the time domain, mainly in the form of convoluted relationship between loads and system responses so as to obtain the time history of loads. In order to obtain the

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forces in the time domain, we need to resort to inverse Fourier transform of the forces computed in the frequency domain. However, the inverse transform is suitable for stable and stationary random forces. Hence, it is rather difficult to identify impact transient forces using frequency domain methods. In contrast, we can identify all types of loads including impact loads using time domain methods. Apart from this, time domain methods, are relatively accurate and free from all transformation errors. Much of the recent research is reported on developing input force identification algorithms based on the time domain.

Most of the existing time domain based input force identification algorithms are based on the state-space formulations [10–12]. In the majority of these algorithms, the Tikhonov regularization technique or its variants [13–15] have been used to solve the formulated inverse problem associated with input force identification. These regularization techniques depend rather heavily on the regularization parameter and either proved non-smooth solutions or over smooth solutions. Further, in the majority of the proposed force identification algorithms, it is difficult to identify input force time history of longer duration. Even though most of the methods yield a good estimate of force time history when the complete time history response of the structure are available and they perform rather poorly when response measurements are not available at all locations. Similarly, many of these techniques exhibit sensitivity to measurement noise.

Further, It should be pointed out here that the force-time history is estimated using all these aforesaid methods with the assumption that the structural parameters (i.e. stiffness, mass, and damping) are known a priori. However, an FE model of a real structure is, in fact, an additional abstraction layer between the actual structure and the identification procedure. Such a model requires updating with identified system parameters (system identification) to realistically estimate the input force time histories. Keeping this in view, several research efforts have earlier been made to simultaneously identify both system parameters and input force using adaptive filters and least-squares approaches and its variant [16–22]. The major limitation of these families of algorithms is that they involve a large number of time-consuming iterations. Some recent efforts have been made to use meta-heuristic algorithms [23] for simultaneous identification of dynamic force and system parameters. However these algorithms are stochastic in nature and with incomplete measurements, noise, unique solutions are sometimes difficult to obtain. Apart from this, stochastic search algorithms are likely to consume more computational time to get solutions with reasonable accuracy and hence not very apt for online identification. Further modelling errors have a great bearing inaccurate identification of input force time history.

Keeping these things in view, we propose a new algorithm based on the dynamic principal component analysis (DPCA) for online identification of input force time history acting on any structure using the acceleration time history data with limited instrumentation. This method does not require to know the system parameters a priori unlike previous methods reported in the literature. Further, we do not require any numerical model for system parameter identification, unlike the previous works. However, we need to initially develop a non-parametric model of the system using the known input and output measurements obtained at varied levels of excitation. We use dynamic principal Component Analysis (DPCA) for this purpose. Later we also use DPCA for online identification of input force excitations on the system. Apart from that, we also investigate the effectiveness of the proposed method with limited instrumentation and measurement noise. We present a PCA based optimal sensor placement algorithm for limited instrumentation and show that it is more effective for load identification problems.

Since the focus of this paper is to develop an online force identification algorithm for their practical application, we have assumed that the points of application of unknown forces are known and the only magnitude needs to be identified. Even though it is possible to identify the spatial location of forces by several methods for an instant by transmissibility [6], SWAT [24], pseudo inverse methods [25], Kalman filter [26], those details are not presented as it will be a deviation from the objective of the paper.

2. Principal component analysis

Principal Component Analysis (PCA) is based on an orthogonal decomposition of the process variables along the direction that explains the maximum variation of the data (the components that contain most of the information) [27,28]. PCA is also used as data reduction tool that is capable of compressing data and reducing its dimensionality so that essential information is retained and made easier to analyse than the original data set. PCA can be accomplished by applying the Singular Value Decomposition (SVD) on discrete packets of sensor data. Using the SVD, a packet of sensor data X ($N \times n$ matrix of data, n samples/data points in time of N different measurements) can be decomposed as

$$X = U \sum V^T \tag{1}$$

where U indicates the principal components (PCs) of size $N \times N$ and V indicates the principal coordinate history of size $n \times n$ respectively which contains the normalized response of the principal directions. The diagonal matrix Σ is termed the singular matrix in which the elements are arranged in the decreasing order of energy present in each mode. In order to characterize the system, we use only a first few singular values based on energy criteria corresponding to 99% of total energy [29–32].

3. Dynamic principal components analysis with overlapped windows (DPCA)

Dynamic Principal Components Analysis [27,28] is similar to PCA. The time necessary to compute the principal components using SVD in the case of PCA increases with the number of measurements. There is a delay in detecting input force