Direct State-Space Models for Time-Varying Sensor Networks

THOMAS J. MATARAZZO and SHAMIM N. PAKZAD

ABSTRACT

This paper discusses data from sensor networks with time-variant configurations called dynamic sensor network (DSN) data, which have a higher capacity for storing spatial information than fixed sensor data. DSN datasets are applicable to high-resolution mobile sensor networks and the processing of BIGDATA. The defining attribute of these data matrices is the presence of spatial discontinuities, which pose a modeling challenge. An indirect state-space model with user-selected states is presented to account for data matrices containing spatial discontinuities. With this approach, measurements from a large number of sensor nodes can be incorporated in a model with a relatively small size. General characteristics of DSN data are provided and a BIGDATA processing example is examined.

INTRODUCTION

Data acquisition and processing in SHM have depended on the use of fixed sensor networks [1–5]. In system identification (SID), this reliance limits the spatial observations in estimated mode shapes [6]. In dense fixed sensor network applications [1, 7–9], once each sensor is instrumented, it maintains its location throughout data collection and generates a single fixed data matrix. For the exception of Matarazzo and Pakzad [6, 10], data from multiple sensor configurations have been split into several data matrices and analyzed separately [11].

The advancement of sensor technologies and the development of approaches for processing new types of data efficiently are motivated by both an improvement in observed structural information and a reduction in network setup efforts. The resulting data often contain inherently different properties than fixed sensor data and create unique processing challenges. Some examples include the mixture data with different sampling rates [12], data with missing observations or data from mobile sensors networks [6], or prohibitively large data dimensions of BIGDATA [13].

Department of Civil and Environmental Engineering, Lehigh University, ATLSS Engineering Research Center, 117 ATLSS Drive, Imbt Labs, Bethlehem, PA 18015, U.S.A.

In this paper, data from time-variant sensing configurations, i.e., dynamic sensor networks (DSNs) are considered. Basically, DSN data combine measurements from numerous sensing arrangements. Through the use of DSN, information from a very large number of sensing nodes can be condensed into a small data matrix. High-resolution mobile sensor networks or BIGDATA can be efficiently represented by DSN data.

PROPERTIES OF TIME-VARIANT SENSOR NETWORKS

When implementing a time-variant sensor network, i.e., DSN, it is essential that the locations of each sensor are known precisely, especially for mobile sensors. The coordinates of the sensors, and in particular, their evolutions in time, are key to decoding the space-time measurements of a DSN dataset for use within a mathematical model.

In the case of a fixed sensor network, the entries of this, so-called sensor-position matrix are identical for all time steps, since the locations of the sensors do not vary with time. For DSN data, the values in the sensor-position matrix, vary with time. Spatial discontinuities are the defining property of DSN data and occur at time steps where the sensors have new positions. For example, sensing locations can vary with time due to sensor mobility; such changes trigger spatial discontinuities in the DSN data matrix, at every new position of the mobile sensor.

ONLINE AND OFFLINE DATA TYPES

Each type of DSN data is characterized by the source of its spatial discontinuities. Online DSN data come from a physical DSN, in other words, a time-varying sensor arrangement that records data, without pause, using several sensing arrangements (groups). In this case, group switches are caused by to the physical motion of sensors during data acquisition. One example of online DSN is high-resolution mobile sensing: relatively few moving sensors scan a very large number of sensing nodes. Sensors shift to new nodes after each sample. The physical motion of this sampling mechanism causes spatial discontinuities in the DSN data matrix at every time step.

Offline DSN data are selected from larger data matrix after data collection. In this case, the DSN is a subset of the measurement population and data parameters are customizable by the user. For example, BIGDATA refers to a *very large* data matrix constructed through the use of an equivalently large number of sensors during data acquisition network. In such cases, it is not possible, nor in many cases is it necessary, to process all of this BIGDATA simultaneously, if at all; even elementary operations such as uploading all measured data for processing could require significant computational efforts [13]. Offline DSN datasets provide a useful technique to is to extract an information-packed subset from the BIGDATA population. A single data matrix can be designed to contain a vast amount of spatial information in a small size. Offline DSN data is highly versatile, there are numerous potential offline DSN datasets available from a single BIGDATA endeavor.

STATE-SPACE MODELING

The inherent spatial discontinuities in DSN data introduce a modeling challenge. Typically, when processing fixed sensor network data, the structural degrees-of-freedom (DOF) in the mathematical model are assigned to be coincident with the sensing nodes. In DSN data, information from many more sensing nodes are available, however, it is not feasible, nor is it necessary in many cases, to assign DOF at all sensing nodes; a simple model which integrates dense spatial information is sought.

The success of the state-space model approach lies within the definition of the state variable [14, 15]. Again, a model including states as the responses at all sensing nodes would be unmanageably large. Instead, states can be assigned to a limited number of DOF that well represent the behavior of the system. Mathematically, such physical states can be assigned through a coordinate transformation. The following model in equations (1 – 5) is derived from the state-space model in modal coordinates. More specifically, the transformation T maps modal states $\mathbf{z}$ to selected physical states $\bar{\mathbf{x}}$ via $\bar{\mathbf{x}} = T\mathbf{z}$. The precise entries of the transformation matrix depend on the physical states chosen by the user; in general, T is comprised of mode shape ordinates.

$$\bar{A} = TA^{\langle M \rangle}T^{-1} \tag{1}$$

$$\bar{B} = TB^{\langle M \rangle} \tag{2}$$

$$\bar{C} = C^{\langle M \rangle}T^{-1} \tag{3}$$

$$\bar{\mathbf{x}}_k = \bar{A}\bar{\mathbf{x}}_{k-1} + \bar{B}\upsilon_{k-1} \tag{4}$$

$$\mathbf{y}_k = \Omega_k \bar{C}\mathbf{x}_k^* \tag{5}$$

Where $A^{\langle M \rangle}$ is the modal state matrix, $B^{\langle M \rangle}$ is the modal state input matrix, υ_{k-1} is the modal input vector, and $C^{\langle M \rangle}$ is the modal observation matrix [16] which are all truncated to M structural modes. The new, transformed model parameters $\bar{A}$, $\bar{B}$, and $\bar{C}$ are in physical coordinates. Lastly, Ω_k is a time-varying matrix which links the responses of the observed sensing nodes, i.e., DSN data $\mathbf{y}$, to the underlying states defined by $\bar{\mathbf{x}}$. This model term is required to correctly incorporate observed DSN data to a given set of underlying physical states.

Two attractive features of this model are its scalability and its versatility. The model's size is not governed by the spatial resolution of the sensor network. The model size is equivalent to that of the modal state-space model, which is often significantly smaller than the number of sensing nodes. Furthermore, user-defined physical state variables enable a high utility for extracting the vast spatial information contained in DSN data. In this model, corresponding mode shapes are the modal ordinates at the locations of the physical states, $\bar{\mathbf{x}}$, which may seem at first, limiting. However, through various definitions of T (consequently new sets of $\bar{\mathbf{x}}$) and repeated model implementations, high-resolution mode shapes can be estimated through SID. In summary, the versatile structure of this family of state-space models offers a technique to retrieve rich spatial information hidden within DSN data, thus maximizing the functions of such sensor networks.

PROCESSING BIGDATA USING MULTIPLE SENSOR GROUPS

The state-space model presented in the previous section is suitable for DSN data, which can be either of the online or offline type. In this section, the processing of offline DSN data from a very dense fixed sensor network is examined. After data acquisition, a very large quantity of data is available, which can be organized as a BIGDATA matrix. Due to computational and storage restrictions, it is difficult or impossible to analyze this data matrix as a whole [13]; however, for many SHM applications, such an analysis is not necessarily required. In other words, it is possible to extract a considerable amount of structural health information without examining every entry of the BIGDATA matrix.

Offline DSN data offer an approach to construct an augmented data matrix, which is significantly smaller than the BIGDATA matrix, yet contains a comparable amount of information about the underlying structural system, e.g., frequency content, or spatial information. The offline DSN data matrix is an information-packed subset selected from the available BIGDATA population.

Consider a simple beam uniformly instrumented with 500 sensors in which the entire fixed sensor network records 2,000 samples of the ambient vibration response; the result is a BIGDATA matrix with 1 million entries. An offline DSN is developed by switching between two sensor groups, each containing four sensors, as pictured in Figure 1. Sensor group 1 includes sensing nodes 1, 2, 499, and 500, while sensor group 2 includes nodes 100, 200, 300, and 400. The first 1,000 samples of the DSN dataset are the measurements of the sensors in group 1. At sample 1,001, a spatial discontinuity occurs, and the measurements from the sensors in group 2 until the end of the DSN dataset. In the DSN data matrix, if the rows indicate time sample, the columns represent observations, which switch between sensing nodes over time.

The sensors included in group 1 are located near the supports of the structure, where the measured responses are expected to be relatively small in magnitude. The sensors in group 2, are uniformly spaced across the beam and are located at nodes with more profitable responses. Due to their arrangement, the measurements for the second sensor group are expected to be significantly larger in magnitude than those for the first sensor group. Equivalently, the values for the second half of the offline DSN dataset are anticipated to be significantly larger than those for the first half of the time series.

In Figure 2, the four DSN data observations are plotted against time along relevant node responses. Basically, each DSN observation switches from the response of one node to another at time step 1,001. For example, at the top of Figure 2, observation 1 is displayed along the responses at nodes 1 and 100. For samples 1 through 1,000, observation 1 follows the response at node 1. At sample 1,001 the observation switches to the response at node 100 until the end of the time series (sample 2,000). Similarly, as depicted in Figure 2, the remaining observations switch from the responses at the nodes assigned in sensor group1 to those in sensor group 2.

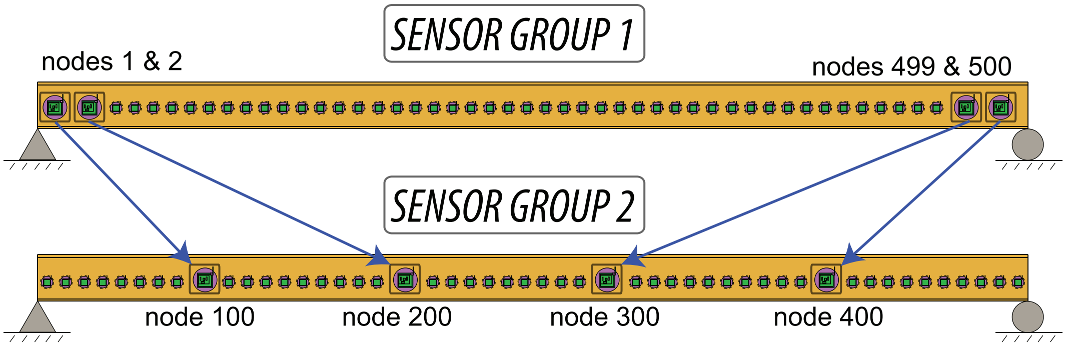

Figure 1. Illustration of sensor groups selected for DSN data out of all BIGDATA

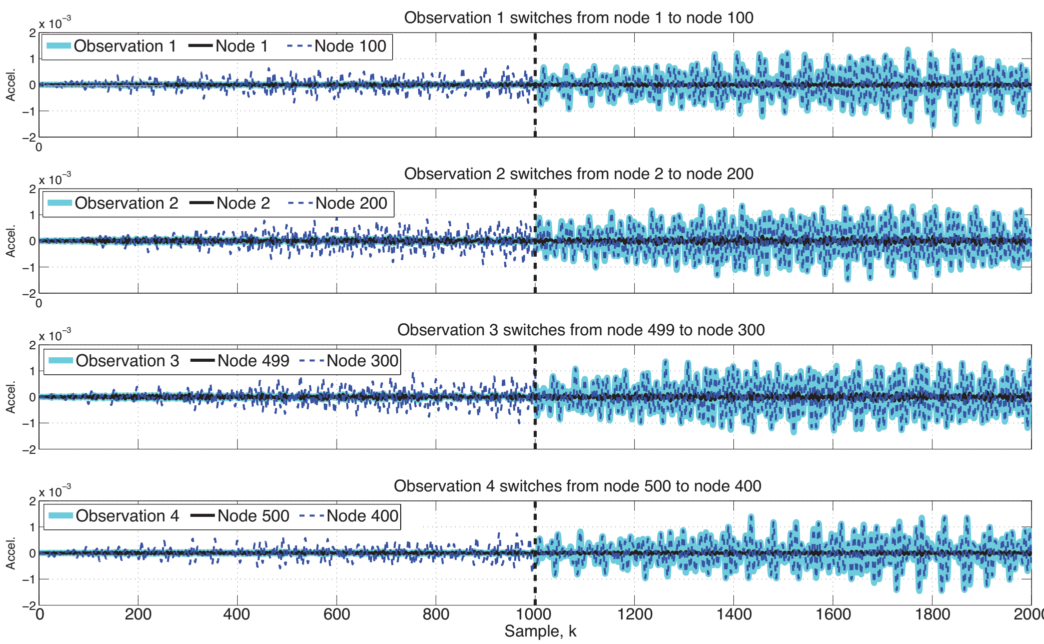

Figure 2. At sample 1,001, observations switch from sensor group one to sensor group two.

The spatial discontinuity in the DSN data at sample 1,001 is evident through inspection of the time series. As expected, the observed values are significantly larger within the latter portion of the DSN data, corresponding to sensing group 2. While this application may seem elementary, the versatility of DSN data and the corresponding state-space approach provide a robust framework for extracting important structural features from time-varying sensor configurations.

CONCLUSION

This paper discussed the use of time-varying sensor configurations in SHM. Such dynamic sensor networks (DSN) provide unique advantages over fixed sensor networks, where sensor locations are time-invariant and contain limited spatial information in many cases. DSN datasets have the ability to condense responses from many sensing nodes into a small matrix size. In short, DSN data matrices have a higher capacity for spatial information than a data matrix from a fixed sensor network.

In order to achieve such high efficiency, DSN datasets include spatial discontinuities, leaving the data initially incompatible with traditional state-space models. A new state-space approach, which transforms a modal model, was presented to properly include DSN data for use within a structural model. The versatility and scalability of the proposed model make it an attractive choice for modeling this class of data since its model size is independent of the spatial resolution of the sensor network. In short, a relatively small model can incorporate data from very many sensing nodes. Furthermore, repeated analyses of a given DSN dataset using different physical states enable the construction of high-resolution mode shapes. An application of BIGDATA processing was provided to showcase the functionality of the model and the advantageous information available within DSN datasets. Through the use of multiple user-defined sensor groups, the user has the ability to develop information-packed datasets while maintaining a small data matrix and manageable model size.

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