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A Wireless Mobile Sensor Platform for Structural Health Monitoring

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ABSTRACT

Modern system identification (SID) procedures rely on fixed sensor networks for data collection. Ideally, sensors are fixed at locations and contain profitable structural responses, however, such sensing areas are often limited by the accessibility of the structure and environmental hazards. Not only are fixed sensor placements limited, the data contains restricted spatial information. Mobile sensors simultaneously record data in time while moving in space, so that few sensors collect data containing dense, less-restricted spatial information, providing a more cost-effective solution than a dense array of static sensors.

Mobile sensor data contain fundamentally different attributes than fixed sensor data. Such data can be classified as dynamic sensor network (DSN) data, which inherently include spatial discontinuities whenever sensors change position. Despite this challenge, such data can be processed for identification using an iterative machine learning technique Structural Identification using Expectation Maximization (STRIDE). Furthermore, the preservation of spatial information in mobile sensor networks has been quantified throughout simulations: given the same number of sensors, a mobile sensor network produces superior spatial information when compared to a static sensor network.

In this paper, ambient vibrations of a simple beam test-bed are measured by a wireless mobile sensor network which includes four parallel lines of motor-driven belts that tow an array of sensor carts along the span of the beam. Feedback between the step motor and a computer was established to achieve a precise spatial grid for the mobile sensors. Modal identification results are presented, documenting the accuracy and feasibility of a real-world mobile sensor network for SID.

KEYWORDS: *Mobile Sensors, Dynamic Sensor Networks, Wireless Sensor Networks, System Identification*

1. INTRODUCTION

System identification (SID) is an important aspect of structural health monitoring (SHM). Through the estimation of structural modal properties, a structure's expected response to dynamic forces can be assessed. The accuracy of modal estimates improves with increased spatial and temporal information, often obtained from a sensor network installed on a vibrating structure (Pakzad et al. 2008; Pakzad and Fenves 2009).

Generally, for fixed sensors, more spatial information can be attained with the use of more sensors. When the quantity of available sensors is limited, optimal sensor techniques can reduce redundant data and improve observed information (Guo 2004; Chang and Pakzad 2014). However, when in pursuit of dense spatial information, the resources available in a fixed sensor network may be insufficient. A high spatial resolution requires either an equivalently large number of sensors or several implementations of a smaller network. The efficiency of increasingly dense sensor networks is reduced by sensor and setup costs, setup and collection times, network reliability, power requirements, and physical limitations due to bridge geometries (Matarazzo and Pakzad 2013; Bagajewicz and Sa 2000). Additionally, preferred fixed sensor locations are not always accessible. Overall, the ultimate flaw of fixed sensors is that they provide restricted spatial information.

Mobile sensor networks offer solutions to the shortcomings of fixed sensor networks (Unnikrishnan and Vetterli 2012; Matarazzo and Pakzad 2015b). With mobile sensing, few sensors can provide rich spatial information. Recent implementations of mobile sensor networks have been diverse, but limited. Zhu et al. (2010) created a sensing device and method that recorded measurements at different nodes, but required stops at each node for data collection. Sibley et al. (2002) and Dantu et al. (2005) implemented Robomote for coverage of large-scale sensor networks for non-SHM applications. Partial system identification (SID) applications have included using frequency-domain techniques for frequency identification in single bridge spans (Lin and Yang 2005; Cerda et al. 2012) and theoretical analyses with limited experimental results (Gonzalez et al. 2009; Gonzalez et al. 2012).

A comprehensive modal identification (one that includes frequency, damping, and mode shape estimates) is sought using a network of mobile sensors that simultaneously move in space while recording data in time. In the following section, the mathematical concepts for extracting modal properties from mobile sensing data are reviewed. Then, the experimental test-bed, wireless mobile sensor platform, and data collection protocol are described. The collected data is analyzed and the system identification results are discussed, followed by concluding remarks.

2. MATHEMATICAL MODEL

2.1. A Truncated Physical Model (TPM) for Mobile Sensing Data

Similar to other new sensing techniques, e.g. data fusion (Smyth and Wu 2007) or SID with incomplete data (Matarazzo and Pakzad 2015b), mobile sensor data contains inherently different attributes in comparison to typical fixed sensor data. In the context of this paper, mobile sensor data is considered a part of the broad class of dynamic sensor network (DSN) data and can be efficiently processed with the Truncated Physical Model (TPM) (Matarazzo and Pakzad 2015c; 2015d), which naturally contains spatial discontinuities whenever sensors change position during data collection. These spatial discontinuities are defined by the paths of the mobile sensors and their sampling frequencies. For details on the characteristics of DSN data and formation of these spatial discontinuities, the reader is referred to (Matarazzo and Pakzad 2015c).

With DSN data, information from a very large number of sensing nodes are available, however, it is not feasible, nor is it necessary in many cases, to select a model with DOF assigned at all sensing nodes. The TPM integrates rich spatial information into a relatively small-sized model.

In general, the definition of the state variable determines the success of the state-space model. A model with states defined as the responses of all sensing nodes would be unmanageably large. In the TPM, the states are defined at user-selected DOF, located where modal ordinates are desired. Mathematically, the truncated physical states are defined by the transformation from modal coordinates to physical coordinates. Equations (1 – 5) are based on the relationship $\bar{\mathbf{x}} = T\mathbf{z}$, where T is the transformation matrix that maps modal states $\mathbf{z}$ to selected physical states $\bar{\mathbf{x}}$. The transformation matrix is comprised of mode shape ordinates at the TPM states (the locations specified by the user). The following TPM model parameters are defined in terms of state-space model parameters for the modal state-space model (Juang and Phan 2001).

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

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

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

$$\mathbf{x}_k^* = A^* \mathbf{x}_{k-1}^* + B^* \eta_{k-1} \tag{4}$$

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

$A^{\langle M \rangle}$ is the modal state matrix, $B^{\langle M \rangle}$ is the modal state input matrix, η_{k-1} is the modal input vector, $C^{\langle M \rangle}$ is the modal observation matrix (Juang and Phan 2001), and υ_k is random measurement noise. The superscript $^{\langle M \rangle}$ indicates modal truncation at structural mode M. The TPM model parameters A^*, B^*, and C^* are in physical coordinates. Lastly, Ω_k is a time-varying, mode shape regression (MSR) matrix that links the responses of the observed sensing nodes, i.e., DSN data $\mathbf{y}$, to the underlying, user-selected states defined by $\mathbf{x}^*$. The MSR term is essential to correctly incorporate observed DSN data in the TPM.

Two attractive features of the TPM 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 defined by the number of modes included in the analysis and is relatively small when considering many sensing nodes. Furthermore, user-defined TPM state variables enable a high utility for extracting the vast spatial information contained in DSN data. In the TPM, corresponding mode shapes are the modal ordinates at the locations of the TPM states, $\mathbf{x}^*$, which are arbitrary. This attribute may seem at first, limiting; however, through various definitions of T (consequently newly defined TPM states $\mathbf{x}^*$) and repeated model implementations, high-resolution mode shapes can be estimated through SID. In summary, the TPM offers a versatile technique for extracting rich spatial information from DSN data.

2.2. IDENTIFICATON OF THE TRUNCATED PHYSICAL MODEL (TPM)

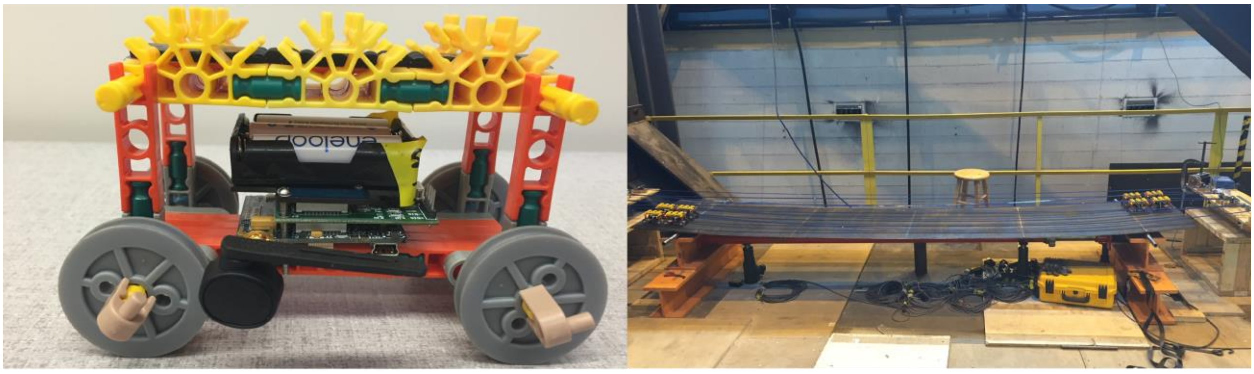
In this section, an overview of the system identification procedure is discussed. The Structural Identification using Expectation Maximization (STRIDE) (Matarazzo and Pakzad 2015a; 2015b) algorithm, tailored for the TPM, was implemented. For brevity, the details of this technique are not explicitly discussed in this paper, but are available in chapter 6 of (Matarazzo and Pakzad 2015c).

STRIDE is used to determine maximum likelihood estimates (MLE) for the TPM model parameters. The algorithm begins with an initial estimate of the model parameters. These parameters are updated iteratively, based on statistics from the expectation step (E-step) and equations in the maximization step (M-step). The significance of the parameters update equations in the M-step is that they are designed to optimize the conditional expectation of the log-likelihood function for the TPM. When the measured slope of the likelihood function becomes practically equal to zero, the algorithm ends, and the final parameter estimates are the MLE.

3. EXPERIMENTAL TESTBED

In this experiment, eight mobile sensing carts scanned a steel beam structure under ambient vibration loading conditions. Four belts, which extended over the span of the beam, towed the sensor carts. These belts were part of a pulley system driven by a computer-controlled motor. The motor was a STAC6-Si model from Applied Motion, controlled by Si Programmer software (Si 2015). The 144-inch steel beam was simply supported with a span of 119.75 inches, serving as a roadway for the mobile sensor carts to move along. The belt tensions were maintained to limit the sag of the top portion and prevent slippage of the bottom. The sensor carts were constructed with molded plastic connector pieces. A rubber friction pad was placed on the roof of each cart to make contact with the bottom of the belts and enable towing. Sensor cart details are shown in Figure 1a; a photograph of the test specimen is provided in Figure 1b.

The wireless sensor within each sensor cart was composed of materials produced by MEMSIC. It consisted of an IPR2420 Imote2 preconfigured with the TinyOS bootloader which used Java to allow for a more reliable and efficient method of gathering data (Pakzad et al. 2008). The code was sent to an IIB2400 interface board where it was debugged with the help of JTAG (Imote2). The IBB2400CA battery board was powered by three 1.2 V batteries, and an ISM400 sensor board collected acceleration data (Spencer 2011) As pictured in Figure 1a, each belt towed two carts, and in the starting position, the wheels of the leading sensor cart were aligned over supports (located 12-1/8 inches from the edge of the beam). Belt pairs rotated in reverse directions, carrying eight sensor carts in total. Two sets of four carts were on each side of the beam. A top view of the setup with pertinent dimensions is in Figure 2.



(a) (b)

Figure 1: Experimental components – (a) A close-up of mobile sensor cart carrying the IBB2400CA battery board, ISM400 sensor board, and IPR2420 Imote2. (b) Beam sits on two rods for simple support, while a motor (at right) allows blue belts to move sensors the length of the beam.

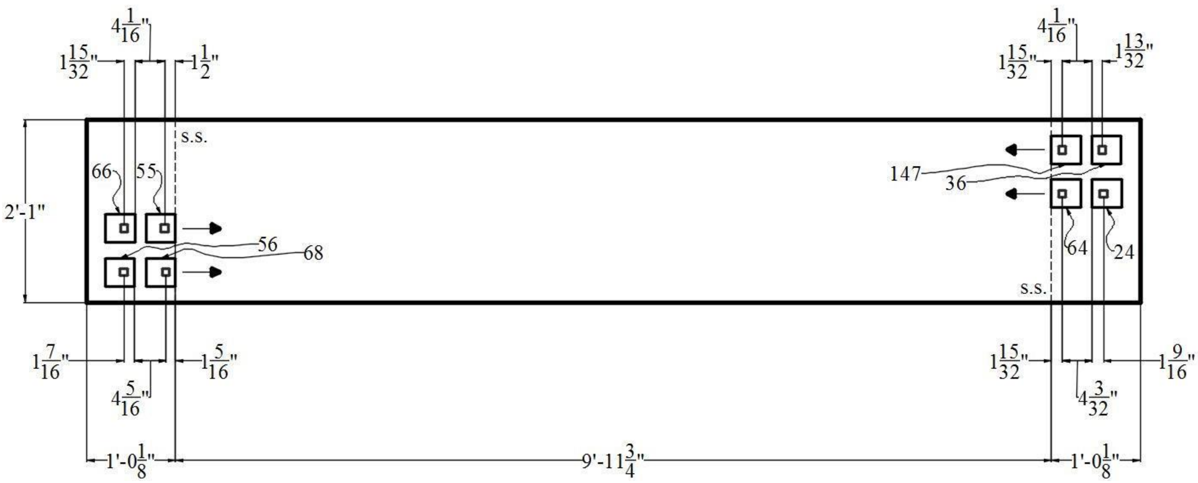


Figure 2: Experimental schematic in plan view with sensor carts in their starting positions – Pertinent dimensions and sensor numbers are provided. The large rectangle is the simply supported beam; squares indicated by 24, 36, 55, 56, 64, 66, 68, and 147 are the sensor carts; smaller squares within the sensor carts represent the accelerometer within the wireless sensors.

With the specimen and pulley system constructed, a custom script was developed using the Si Programmer to control the rotation of the motor and therefore the paths of the mobile sensors. In this protocol, sensor carts were pulled at a speed of 4.5 inches/second for a total of 129.3 inches, then the direction of the motors reversed so that sensor carts returned to their starting positions. The distance of 129.3 inches permitted all sensor carts to traverse the entire span of the beam. The beam vibrated in ambient conditions while the sensor carts moved across the beam and recorded accelerations at rate 280 Hz. Sensor network data was retrieved using the computer program Cygwin Bash Shell (by Cygnus Solutions) and then imported into MATLAB for data analysis.

4. RESULTS AND DISCUSSION

Figure 4 provides the power spectral density estimate for a representative mobile sensor up to 30 Hz. There are a few distinct peaks within this figure, which indicate the presence of natural vibration modes in the data.

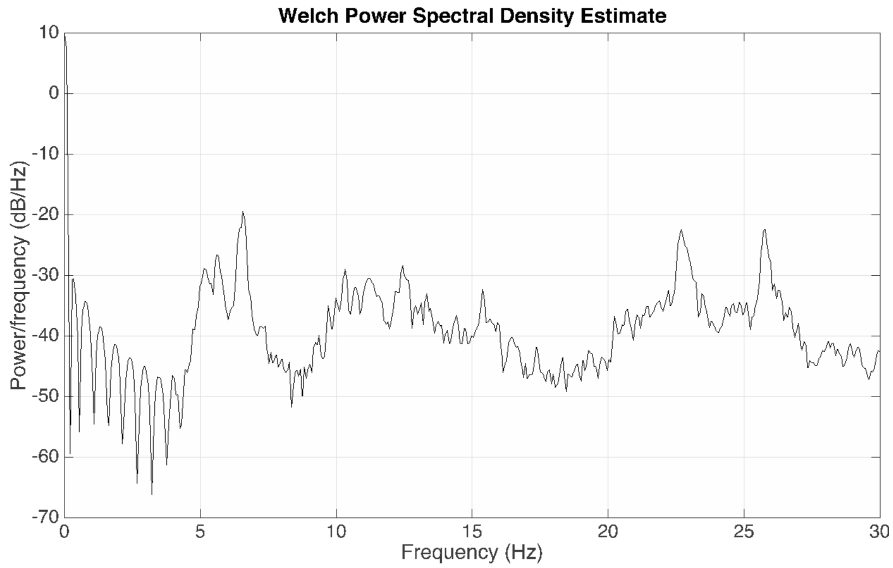


Figure 4: Power spectral density of a mobile sensor estimated by Welch's Method

The STRIDE analysis of the mobile sensor data was implemented for five different sets of TPM states. As a result, modal coordinates for twenty-two different beam locations were identified. Using data from only six out of eight sensors, the STRIDE algorithm identified three vertical modes and one torsional mode, with frequencies that aligned well with the peaks in Figure 4. The identified modal frequencies, damping ratios, and shapes are provided in Figure 5. STRIDE estimated vertical frequencies to be 5.18 Hz, 11.6 Hz, and 25.9 Hz, and identified the torsional frequency as 6.43 Hz.

However, frequency information can arguably be obtained directly from inspection of the power spectrum. The novelty within the TPM and STRIDE lies within the ability to extract the rich spatial information hidden within the mobile sensor data. The mode shapes in Figure 5 contain twenty-two modal estimates from only six sensors. Twenty-two fixed sensors (or multiple outings with fewer sensors) would be required to achieve this spatial resolution. To reiterate, fixed sensors contain singular spatial information. In these results, it is evident that the mobile sensor data is capable of efficiently storing information for many points on the structure.

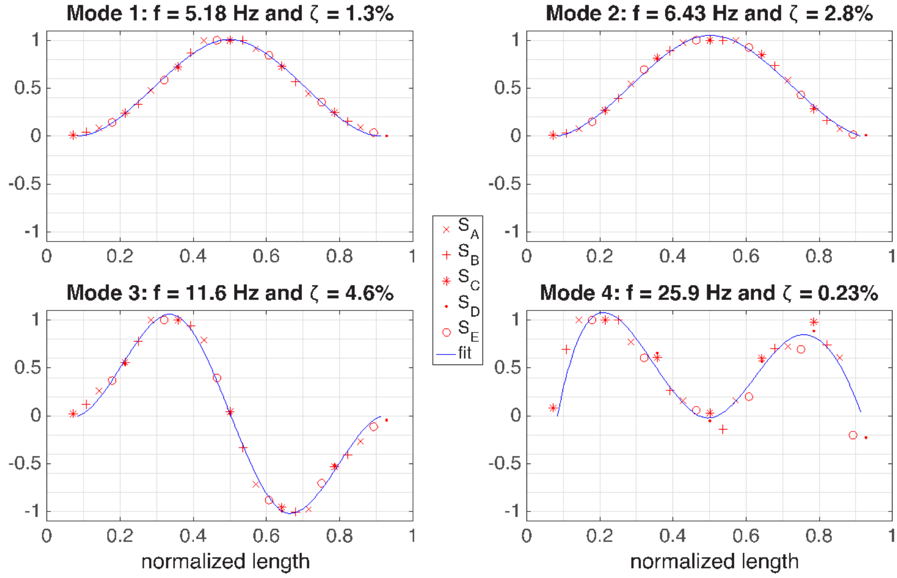


Figure 5: Four identified frequencies, damping ratios, and mode shapes

5. CONCLUSION

In this paper, a mobile sensing platform was developed with the immediate goal of identifying frequencies, damping, and mode shapes of a structural system from wireless accelerometer data. The Truncated Physical Model (TPM) required to process mobile sensor data was discussed and the Structural Identification using Expectation Maximization (STRIDE) algorithm was selected to identify the model parameters. Eight moving sensor carts, each equipped with a wireless sensor, were towed over the span of a simply supported steel beam by four parallel belts in a motor-driven pulley system. The two pairs of belts, each towing two sensors, were constructed to revolve in reverse directions, so that sensors traveled in opposing directions, similar to traffic on a highway.

Using the mathematical tools outlined in this paper, three vertical modes and one torsional mode were identified from the mobile sensor data. The novelty within the TPM and STRIDE is the ability to extract the rich spatial information hidden within the mobile sensor data. Using data from only six of the eight sensors, mode shapes with twenty-two ordinates were constructed. Twenty-two fixed sensors would have been necessary to achieve spatial resolution comparable to the results in Figure 5.This study further quantified the superior spatial information provided by mobile sensors and used experimental data to validate the applicability of STRIDE to the TPM.

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