Integrating Pre-Existing Telecommunication Fiber Cable Vibration Sensing and Drive-by Vehicle Vibration Sensing for Scalable Bridge Health Monitoring

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ABSTRACT

We introduce a novel and scalable bridge health monitoring approach by combining pre-existing telecommunication fiber vibration sensing and drive-by vehicle vibration sensing. Many bridges have pre-existing telecommunication fiber cables crossing in conduits, which can function as a distributed acoustic sensing system to continuously record bridge dynamic strain responses in high spatiotemporal resolution. In addition, the drive-by vehicle vibrations capture the information of the input load to the bridge and the interactive bridge vibrations with high spatial resolution. Our approach integrates the two sensing systems to offer complementary input-output information and insights into bridge conditions. It estimates bridge modal properties by modeling the vehicle-bridge-fiber interaction with an augmented state-space model. The model considers the bridge dynamics and input loads as a joint state observed by the telecommunication fiber vibration and drive-by vehicle vibration sensing systems, respectively. Our approach is scalable as it does not require on-site installation and maintenance of sensing systems on the bridge. It is also more accurate than using a single sensing system because it takes into account both the input and output signals of the system being analyzed. We evaluate our approach with real-world experiments on a steel stringer/multi-beam bridge in Palo Alto, California, with telecommunication fiber cables running under the deck. Our approach successfully estimates bridge dynamic properties, including natural frequency, damping ratio, and mode shape. It outperforms a baseline method that only uses telecommunication fiber vibrations, which indicates the potential for accurate and scalable bridge health monitoring.

INTRODUCTION

Bridges are crucial infrastructure systems that connect cities and communities. However, their continuous exposure to traffic, environmental loads, and natural disasters can cause structural damage. For instance, in the United States, around 140,000, or 22% of the more than 617,000 bridges were classified as structurally deficient or functionally obsolete in 2019 [1]. Detecting and repairing damage in its initial phases is crucial to

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prevent more severe damage and potential collapses that could result in substantial financial and human losses. Therefore, developing effective and efficient methods for bridge health monitoring (BHM) is essential to ensure bridges' safety and integrity.

Manual inspection and fixed-sensor-based methods are existing approaches to assess bridge health conditions, but they are not easily scalable due to high labor and installation costs, especially for large bridge networks [2]. To address these challenges, two new BHM approaches have been recently introduced. The latest drive-by vehicle vibration-based BHM can capture the dynamic responses of multiple bridges with a single drive-by vehicle, increasing scalability and efficiency [3, 4]. Additionally, telecommunication optical fiber cables have been turned into distributed acoustic sensing (DAS) systems, which are long-offset virtual and dynamic strain sensor arrays with high temporal and spatial resolution. These extensively installed telecommunication fiber cables utilize pipes and conduits installed on bridges to span rivers and roads, making them easily accessible for BHM [5]. Both the drive-by vehicle vibration sensing and telecommunication fiber vibration sensing are non-dedicated and do not require on-site installation and maintenance of sensing systems on bridges. This feature makes these BHM systems scalable, cost-effective, and applicable to various types of bridges. Moreover, they can be easily integrated into existing infrastructure, enhancing their practicality and effectiveness.

However, the two novel BHM systems have their own limitations. While drive-by vehicle vibration data can offer valuable insights into the bridge condition, it only provides limited temporal information at each position on the bridge. As a result, this limited temporal information limitation may hinder the accurate estimation of the bridge's overall condition. On the other hand, while the bridge vibrations measured by the telecommunication fiber cables are in high spatiotemporal resolution, they are indirectly measured and thus subject to larger measurement noise and uncertainties compared to direct measurements from well-calibrated bridge sensors, such as strain gauges and accelerometers. Due to the absence of input load measurements, only relying on output measurements of the bridge results in less accurate estimation/identification of the bridge properties compared to input-output methods.

To address these challenges, we introduce a new BHM approach that integrates drive-by vehicle sensing and pre-existing telecommunication fiber cable sensing to provide complementary input and output information about the bridge dynamics. Our approach analyzes three components: the bridge, the pre-existing telecommunication fiber cables, and the drive-by vehicles. These three components interact with each other to form a complex vehicle-bridge-fiber interaction system. Especially, both the bridge dynamic responses and the input vehicle loads are not directly measured. The telecommunication fiber sensing system continuously records the bridge's dynamic strain responses induced by traffic and environmental loads, while drive-by vehicle vibrations capture the input loading information with high spatial resolution. To model this complex interaction system, we introduce an augmented state-space formulation. This formulation considers the bridge's dynamic state and the input load as an augmented state, which are measured/observed through the telecommunication fiber and drive-by vehicle sensing systems, respectively.

Furthermore, a two-step system identification method is introduced to estimate various bridge dynamic properties, including natural frequency, damping ratio, and mode shape. To approximate the load applied on the discretized bridge model due to the drive-by vehicle, the first step of our method transforms the measured drive-by vehicle vibrations into nodal forces at the degrees of freedom of the bridge with the cubic Hermitian interpolation [6]. Then, the data-driven stochastic subspace identification algorithm (SSI-data) [7] is employed to estimate the bridge's dynamic properties given a set of telecommunication fiber responses and nodal forces converted from the drive-by vehicle vibration responses. SSI-data is a suitable method for our approach because it does not require (non-linear) optimization techniques needed by other methods, such as the prediction error minimization [8].

We conducted a real-world experiment to evaluate the effectiveness of our approach on a steel stringer/multi-beam bridge located in Palo Alto, California, with telecommunication fiber cables installed under the deck and an instrumented drive-by vehicle. The results showed that our approach successfully estimated the bridge's first-mode natural frequency with a mean absolute percentage error (MAPE) of 1.281%, damping ratio with an 18.22% MAPE, and mode shape with a 19.33% modal assurance criterion error. Our approach yields approximately two times MAPE error reduction for natural frequency and 1.5 times MAPE error reduction for damping ratio compared to a baseline method that solely relies on telecommunication fiber vibrations. The improved estimates obtained using our novel method lead to a better assessment of the bridge's health condition. The successful implementation of our approach demonstrates the feasibility of using integrated pre-existing telecommunication fiber vibration sensing and drive-by vehicle vibration sensing for bridge health monitoring.

BHM WITH INTEGRATED TELECOMMUNICATION FIBER VIBRATION SENSING AND DRIVE-BY VEHICLE VIBRATION SENSING

This section presents our BHM approach that integrates vibration responses from telecommunication fiber cables and the drive-by vehicle. An augmented state-space model is introduced to formulate the vehicle-bridge-fiber interaction system, followed by a two-step method to identify this system.

An Augmented State-Space Model Formulating the Vehicle-Bridge-Fiber Interaction System

In this study, we analyze the interaction between a vehicle, a bridge, and a telecommunication fiber cable. This interaction considers how the dynamics of the bridge are induced by the moving vehicle loads and measured/observed by the telecommunication fiber sensing system. The analysis model adopted to formulate the vehicle-bridge interaction is a simply-supported beam subjected to moving loads due to the traffic. The equation of motion for the vertical motion of the linear system simulated through a finite element model is

$$\mathbf{M}\ddot{\mathbf{z}}(t) + \mathbf{C}\dot{\mathbf{z}}(t) + \mathbf{K}\mathbf{z}(t) = \mathbf{S}(x)\mathbf{u}(t), \tag{1}$$

where $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ denote the mass, damping, and stiffness matrices, respectively; $\mathbf{z}(t)$ is the vector of vertical displacement, corresponding to the finite model degrees of freedom (DoFs); $\mathbf{u}(t)$ is the input vector, and $\mathbf{S}(x)$ is the input delta matrix that indicates where loads are applied. The input vector consists of the static moving loads due to vehicles' self-weights and the dynamic loads due to vehicles' vibrations.

Furthermore, the state-space representation is employed to formulate the vehicle-bridge-fiber interaction:

$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) \\ \mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{u}(t), \end{cases} \tag{2}$$

where $\mathbf{x}(t) = [\mathbf{z}(t), \dot{\mathbf{z}(t)}]^T$ is the state vector; $\mathbf{A}$ and $\mathbf{B}$ are system and input matrices, respectively:

$$\mathbf{A} = \begin{bmatrix} 0, & I \\ -\mathbf{M}^{-1}\mathbf{K} & -\mathbf{M}^{-1}\mathbf{C} \end{bmatrix} \qquad \mathbf{B} = \begin{bmatrix} 0 \\ \mathbf{M}^{-1}\mathbf{S} \end{bmatrix},$$

The second equation of Eq. (2) formulates the bridge-fiber interaction. $\mathbf{y}$ is the observation vector. $\mathbf{C}$ and $\mathbf{D}$ are output/observation and feedforward matrices, respectively:

$$\mathbf{C} = \begin{bmatrix} \mathbf{S}_\epsilon, & 0 \end{bmatrix} \qquad \mathbf{D} = \begin{bmatrix} 0 \\ \mathbf{S}_a\mathbf{M}^{-1}\mathbf{S} \end{bmatrix},$$

where $\mathbf{S}_\epsilon$ and $\mathbf{S}_a$ are the conversion matrices for strain and acceleration measurements, respectively.

Because the system input, $\mathbf{u}(t)$, is indirectly observed through measuring the drive-by vehicle vibrations, an augmented state-space model [9] is employed:

$$\begin{cases} \dot{\mathbf{x}}^a(t) = \mathbf{A}^a\mathbf{x}^a(t) + \mathbf{w}(t) \\ \mathbf{y}^a(t) = \mathbf{C}^a\mathbf{x}^a(t) + \mathbf{v}(t), \end{cases} \qquad \mathbf{A}^a = \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ 0 & \mathbf{I} \end{bmatrix} \qquad \mathbf{C}^a = \begin{bmatrix} \mathbf{C} & \mathbf{D} \\ 0 & \mathbf{I} \end{bmatrix} \tag{3}$$

where $\mathbf{x}^a = [\mathbf{x}, \mathbf{u}]^T$ is the augmented state vector; $\mathbf{w}(t)$ and $\mathbf{v}(t)$ are the state noise and observation noise, respectively. Then, the continuous-time state-space model is converted to discrete-time with the time step Δt by holding each sample value for one sample interval (i.e., zero-order hold [10]) and through assuming the input random-walk model [11]: $\mathbf{u}_k = \mathbf{u}_{k-1} + \mathbf{w}^u_{k-1}$, where $\mathbf{w}^u_{k-1}$ is a vector of zero-mean white uncorrelated processes. With this augmented state-space model, both the bridge dynamics and indirectly observed loads are considered as states, and the augmented observation, $\mathbf{y}^a(t)$, measured by the telecommunication fiber and drive-by vehicle sensing systems is used to identify the system.

Vehicle-Bridge-Fiber Interaction System Identification

This sub-section presents a two-step method, illustrated in Figure 1, to estimate the properties of the vehicle-bridge-fiber interaction system formulated by the augmented state-space model. In the first step of the method, the moving load caused by the drive-by vehicle is transformed into nodal forces. The second step estimates system matrices and properties of the augmented state-space model.

TRANSFORMING MOVING LOADS INTO NODAL FORCES

To approximate the continuous load applied on the discretized finite element model, the moving loads that are indirectly measured through the drive-by vehicle vibration

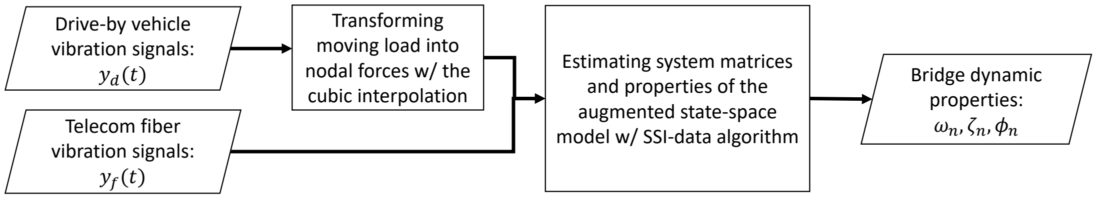


Figure 1. The flowchart of our vehicle-bridge-fiber interaction system identification method that integrates pre-existing telecommunication fiber and drive-by vehicle vibrations.

sensing system are transformed into nodal forces, $\mathbf{y}_n(t)$, at the DoFs of the bridge model. This approximation is performed by interpolating the measured moving loads on each element with the cubic Hermitian interpolation functions [6]:

$$\mathbf{y}_d^n(t) = \mathbf{N}_c(x_c)\mathbf{y}_d^e(t),$$

where $\mathbf{y}_d^n(t)$ is the nodal force at the nth node of the finite element model; $\mathbf{y}_d^e(t)$ is the moving load vector on element e measured by the drive-by vehicle sensing system; $\mathbf{N}_c(x_c)$ is the cubic Hermitian interpolation function evaluated at the moving load contact location x_c. Then, the nodal forces at the DoFs of the bridge model are calculated: $\mathbf{y}_n(t) = \sum_n \mathbf{y}_d^n(t)$. The augmented observation is formed by stacking the telecommunication fiber vibration signals, $\mathbf{y}_f(t)$, and the approximated nodal forces, $\mathbf{y}_n(t)$: $\mathbf{y}^a(t) = [\mathbf{y}_f(t), \mathbf{y}_n(t)]^T$.

ESTIMATING SYSTEM PROPERTIES OF THE AUGMENTED STATE-SPACE MODEL

The data-driven stochastic subspace identification algorithm (SSI-data) [7] is employed to estimate the dynamic properties of the augmented state-space model (Eq. 3). The SSI-data algorithm estimates the stochastic linear system (e.g., estimating $\mathbf{A}^a$ and $\mathbf{C}^a$) given a set of output measurements. It proceeds with projecting the row space of the future output into the row space of the past output. The dynamic properties of the system are characterized by performing an eigenvalue decomposition of the system matrix, $\hat{\mathbf{A}}^a = \mathbf{\Psi\Lambda\Psi}^{-1}$:

$$\omega_n = |\lambda_n|, \quad \zeta_n = -\lambda_n^R/|\lambda_n|, \quad \mathbf{\Phi} = \hat{\mathbf{C}}^a\mathbf{\Psi} \tag{4}$$

where ω_n is the natural frequency of mode n; $\lambda_n = \ln(\mathbf{\Lambda}_{nn})/\Delta t$ is the n-th eigenvalue in continuous time; λ_n^R is the real part of λ_n; ζ_n is the damping ratio of mode n; $\mathbf{\Phi}$ is the mode shape matrix with each column ϕ_n being the mode shape of mode n. Note that we only estimate the first-mode properties in this study.

FIELD EVALUATION

This section presents our field evaluation results of the introduced approach with field experiments on a 28-meter-long bridge in Palo Alto, California.

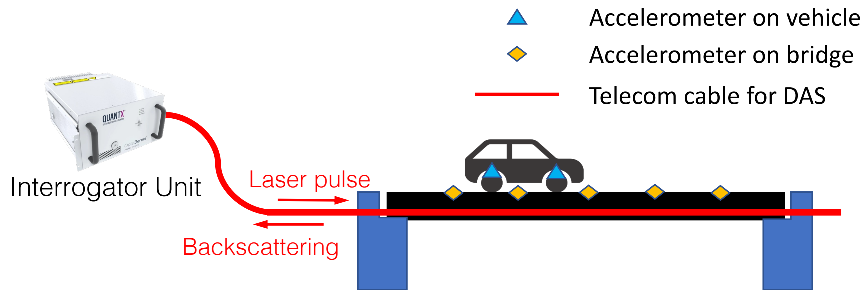
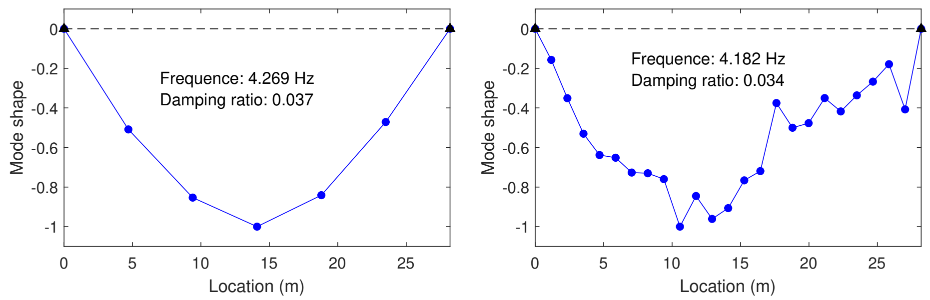


Figure 2. A representation of our sensing deployment on the bridge and the drive-by vehicle.



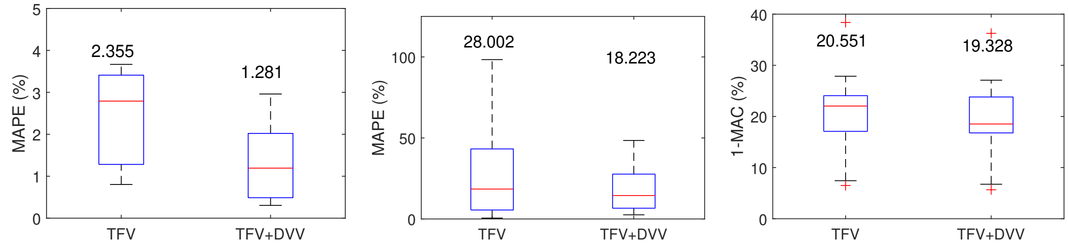
(a)

(b)

Figure 3. The first order mode shape of the testbed bridge estimated using (a) conventional accelerometers on the bridge and (b) our approach. The estimated first-order natural frequency and damping ratio using the conventional approach are 4.269 Hz and 0.037, respectively. The estimated first-order natural frequency and damping ratio using our approach are 4.182 Hz and 0.030, respectively. The modal assurance criterion between the two estimated mode shapes is 0.933.

Experimental Setup and Data Description

The testbed bridge used in our field evaluation is a steel stringer/multi-beam bridge with a length of 28 meters, accommodating two-lane, two-way traffic and walkways. A representation of our sensing deployment on the bridge is shown in Figure 2. Telecommunication fiber cables run in a conduit beneath the bridge deck. An Optasense QuantX DAS interrogator [12] that was installed around 2 kilometers away from the bridge performed distributed acoustic sensing on the bridge with a 200 Hz sampling rate. We chose a 4-meter gauge length and a 1-meter channel spacing in our approach to obtain fine-grained bridge dynamic information with an adequate signal-to-noise ratio for accurate bridge health monitoring. To collect vehicle vibration signals, we installed four PCB 354C03 accelerometers [13] on the wheels of a test vehicle, which was driven across the bridge. Additionally, we installed five PCB 354C03 accelerometers on each one-sixth span of the bridge deck to measure the vertical acceleration of the bridge, which served as validation signals for our BHM approach. During the experiments, we collected eleven sets of telecommunication fiber vibration and drive-by vehicle vibration signals.



(a) (b) (c)

Figure 4. Performance metrics of (a) the bridge natural frequency and (b) damping ratio, and (c) mode shape using telecommunication fiber vibration signals during the test vehicle driving by (TFV) and our integrated telecommunication fiber and drive-by vehicle vibration signals (TFV+DVV). The number above each bar indicates the mean error for the eleven datasets.

Evaluation Results

The accuracy of our approach in estimating bridge dynamic properties is validated by comparing our results with those obtained from conventional accelerometers installed on the bridge deck. The SSI-data algorithm is also applied to the bridge vibration data to provide the ground truth of bridge dynamic properties. Figure 3 (a) shows the first-order mode shape of the testbed bridge estimated using the conventional accelerometers placed on the bridge. The first-order natural frequency of the bridge and the damping ratio is 4.269 Hz and 0.037, respectively.

Figure 4 shows the mean absolute percentage errors (MAPE) of natural frequency and damping ratio estimations and the modal assurance criterion errors (1-MAC) for the eleven datasets using our approach (TFV+DVV) and a baseline method (TFV). “TFV” uses only the telecommunication fiber vibration signals during the test vehicle driving by. Figure 3 (b) shows the first-order mode shape of the testbed bridge estimated using our approach (TFV+DVV). The mean values of the estimated first-order natural frequency of the bridge and the damping ratio are 4.295 Hz and 0.030, respectively. Our approach outperforms the baseline method by achieving 1.281% MAPE for estimating bridge natural frequency, 18.22% MAPE for estimating the damping ratio, and 19.33% MAC error for estimating the mode shape.

CONCLUDING REMARKS

This paper introduces a scalable bridge health monitoring approach that integrates two non-dedicated sensing systems, namely telecommunication fiber vibration sensing and drive-by vehicle vibration sensing. The two sensing systems provide input-output information to complement each other. Our approach estimates bridge modal properties by modeling the vehicle-bridge-fiber interaction with an augmented state-space model that considers the bridge dynamics and input traffic loads as a joint state observed by the two sensing systems. Our approach is cost-effective as it does not require on-site installation and maintenance of sensors and equipment by taking advantage of pre-existing telecommunication fiber cables and drive-by vehicles. We evaluated our approach with a steel stringer/multi-beam bridge and validated our estimations with a conventional accelerometer system. Our approach outperforms a baseline method that only uses telecommunication fiber vibrations in identifying the first natural frequency, damping ratio, and mode shape of the bridge.

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