Vehicle-invariant Drive-by Monitoring Across Multiple Bridges through Bootstrapping-enhanced Unsupervised Domain Adaptation

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ABSTRACT

Bridge health monitoring (BHM) is important to detect damages in the early stages to avoid loss of human life and any disruption in the continuous bridge operations. Drive-by vehicle-based BHM approaches provide more scalable monitoring as compared to manual inspection and fixed sensors on bridges. Each vehicle can pass multiple bridges and can be used for monitoring multiple bridges. In our prior work, we developed a method that can diagnose damage in multiple bridges while eliminating the burden of collecting labeled data from all the bridges. It is achieved by learning features that are sensitive to damage and invariant across bridges. However, in real-world scenarios, vehicles passing the bridge possess varying properties such as suspension system, driving speed, and vehicle mass. Since the vibration signal obtained from the vehicle depends on the vehicle's properties, these variabilities in vehicle properties lead to inaccurate damage prediction of the bridge even for the same damage state.

To overcome these challenges, we introduce a Bootstrapping-enhanced Vehicle - Bridge-Invariant (BeVBI) approach for robust drive-by BHM. It reduces the vibration signal variation due to varying vehicle properties through bootstrapping-based mean estimations. Specifically, vibration signals obtained from vehicles (with varying vehicle properties) passing the bridge are randomly aggregated with replacement (i.e., bootstrapping) and averaged. Based on the central limit theorem, averaging the aggregated signals (bootstrapped signals) reduces signal variability due to vehicle properties by the square root of the number of aggregated signals. Further, these bootstrapped signals are used to predict the damage on multiple bridges by adopting an unsupervised domain learning algorithm. The performance of the above approach is evaluated using a numerical vehicle bridge interaction dataset with two different bridges and 4800 drive-by vehicles having different dynamic properties and speeds. Our approach is successful in diagnosing multiple bridges while being robust to varying vehicle properties. It performs 1.45x better in the detection and localization of damage and 1.75x better in the quantification of damage as compared to baseline methods (MCNN and HierMUD).

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INTRODUCTION

With the growing number of aging bridges, there is an increasing demand to develop a bridge health monitoring (BHM) method that is scalable and effective. Further, the method should be able to detect damage in the early stage across multiple bridges to avoid loss of human life and any disruptions in the continuous operations of the city. Conventionally, bridge assessment is done via manual inspection that requires skilled personnel to inspect the bridge. However, this method is not scalable due to high labor costs and failure to detect damage in the early stages. To address this challenge, fixed sensors-based BHM techniques have been developed which can detect the damage in the early stages on the bridge [1,2]. However, the installation and regular on-site maintenance of the sensors cause traffic interruptions and make this method hard to scale up.

On the other hand, drive-by BHM provides a scalable approach as it uses vehicle vibration passing the bridge to monitor the bridge's health. Existing drive-by BHM approaches can be categorized into bridge modal parameter estimation and data-driven approaches. The bridge modal parameter estimation approach uses vehicle vibration signal to estimate modal parameters of the bridge, such as modal frequencies, mode shape, and damping to detect the damage on the bridge [3]. However, many of these methods estimate parameters by making simplified assumptions such as Euler-beam theory and a simply supported beam that may not hold true with real-world data. Further, these methods require prior knowledge about bridge properties to accurately estimate modal parameters [4]. Data-driven approaches use signal processing and machine learning techniques to detect damage on the bridge. These methods extract damage-informative features that can diagnose damage more effectively [4–7]. Liu et al. developed a method that can diagnose multiple bridges without requiring the labeled data from all the bridges [8]. It transfers the damage diagnosis model learned for one bridge to predict the damage on another bridge and tackles the data distribution shift challenges in extracted features due to the diverse properties of bridges. However, the vibration signal obtained from the vehicle also depends on the vehicle's properties. In real-world scenarios, all the vehicles passing the specific bridge may not possess similar dynamic properties, including suspension system, mass, configurations, and driving speeds. Due to these varying vehicle properties, the damage predictions for the signals are different even though they belong to the same damage state. This leads to inaccurate prediction and hinders the damage diagnosis performance.

To overcome these challenges, we introduce a Bootstrapping-enhanced Vehicle - Bridge-Invariant (BeVBI) for robust drive-by BHM. It reduces the vibration signal variation due to varying vehicle properties through bootstrapping-based mean estimations. Specifically, our approach involves three steps: 1) spatial interpolation of the signal for the reduction of vehicle speed variation, 2) bootstrapping of the signal for the reduction of vehicle property variation, and 3) damage prediction on multiple bridges. Firstly, due to the varying speeds of the vehicle, the signal length of vehicles passing the bridge varies. Moreover, these signals are sampled at different sets of spatial locations on the bridge. Spatial interpolation provides the vibration of the vehicle at equally spaced spatial locations on the bridge, making the length and location of the signal on the bridge consistent. Secondly, the vibration signal characteristics depend on the vehicle's properties. The variability in vehicle properties hinders the learning algorithm's ability to accurately predict the damage on the bridge even for the same damage state. To reduce the effect of vehicle properties, these signals are aggregated randomly with replacement (i.e., bootstrapped), and a new sample is generated by averaging the aggregated bootstrapped signals. According to the central limit theorem, variation in vibration signal due to vehicle properties can be reduced by the square root of the number of aggregated signals. Lastly, these newly generated signals are used to diagnose damage on multiple bridges by adopting an unsupervised domain adaptation learning algorithm [8]. This algorithm transfers the learned damage diagnosis model from one bridge to predict damage on the new bridge without requiring the new bridge damage labels. It learns features that are damage informative and bridge invariant in an adversarial way.

The performance of our approach is evaluated on a numerical vehicle bridge interaction dataset [5]. This dataset includes two bridges with different lengths and vehicles with varying dynamic properties and speeds ranging from 30 to 80 Km/hr. Our approach achieved an accuracy of 99% in damage detection, 99% in damage localization, and 91% in damage quantification on the bridge without requiring its damage labels. Our approach is 1.45x better in the detection and localization of damage and 1.75x better in the quantification of damage as compared to baseline methods (MCNN and HierMUD).

BOOTSTRAPPING-ENHANCED VEHICLE-BRIDGE-INVARIANT (BEVBI) BRIDGE HEALTH MONITORING

In this section, we describe our Bootstrapping-enhanced Vehicle-Bridge-Invariant (BeVBI) approach that consists of 3 modules as shown in Figure 1: Spatial interpolation for reduction of speed variation, bootstrapping for reduction of vehicle property variation, and damage prediction on multiple bridges.

Spatial interpolation for reduction of speed variation

To ensure the consistent length and spatial location of the vibration signal on the bridge due to varying vehicle speeds, the vehicle vibration signal is chopped and interpolated at fixed spatial locations for a specific bridge. Firstly, the vehicle vibration signal over the bridge is extracted by chopping the vehicle vibration signal from the moment the vehicle reaches the start of the bridge until it reaches the end. This is because vehicle vibration signals are obtained by running the vehicle on the ramp before it passes the bridge. However, it contains valuable information about the bridge when the vehicle is over the bridge. Secondly, the signal is interpolated to equally spaced locations along the bridge using spline interpolation. Due to varying vehicle speeds, time-domain vehicle vibration signals have different lengths. Further, each signal corresponds to vibrations obtained at a different set of spatial locations on the bridge. For bootstrapping, each data point in the vibration signal needs to represent consistent information such as vibration at the same spatial location on the bridge. This also ensures the same length of the input is fed into our unsupervised domain adaptation learning algorithm, which is required for our learning algorithm.

Bootstrapping for reduction of vehicle properties variation

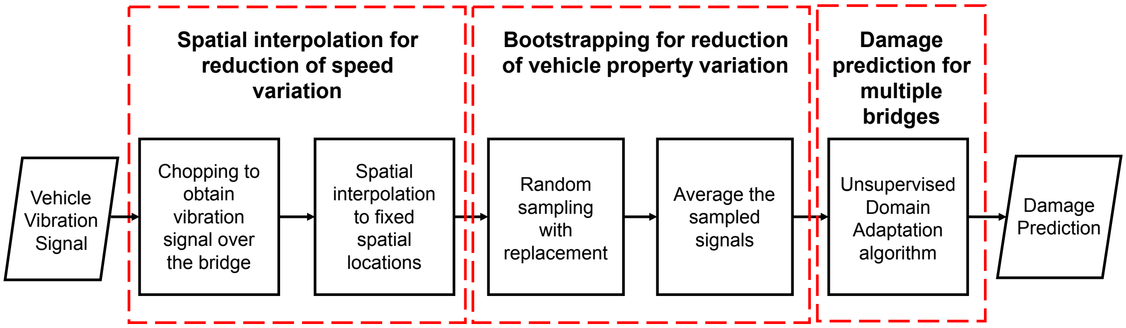


Figure 1. BeVBI System Overview

To reduce the vibration signal variation due to the varying vehicle properties obtained from the specific bridge, the mean signal is estimated from the bootstrapped signals. Vehicle vibration signals obtained for the specific bridge depend on vehicle properties such as speed, mass, suspension system, and bridge dynamic properties. The variability in vehicle properties hinders the learning algorithm's ability to accurately predict the damage on the bridge even for the same damage state. Therefore, to reduce the signal variability due to varying vehicle properties, we first aggregate the vibration signals randomly with replacement through bootstrapping and then, average the aggregated signals to generate the new signal. According to the central limit theorem, averaging the bootstrapped signals reduces the signal variations due to varying vehicle properties by the square root of the aggregated random signals. Here, we assume the speed, mass, and suspension system of the vehicle to be independent and identically distributed random variables. In particular, the vibration signals from each bridge are divided into N_1 and N_2, training and testing events subsets. Then, N_{train} and N_{test} new samples are generated by averaging the X randomly sampled with replacement from training and testing subsets, respectively. Note that N_1 and N_2 should be greater than the number, X.

Damage prediction on multiple bridges

To extract the features that are invariant across multiple bridges (bridge-invariant) as well as informative for various damage states (damage-informative), we adopt an unsupervised domain adaptation learning algorithm approach [9]. This learning algorithm transfers the damage diagnosis model learned from one bridge with known damage labels (source bridge) to predict damage on another bridge with unknown damage labels (target bridge) [8]. This algorithm compromises 3 main components: Hierarchical feature extractors, task predictors, and domain classifiers. The bootstrapping-based mean estimated signals are used to extract damage-informative features by the hierarchical feature extractors. Task predictors use these extracted features to predict the damage task label. Further, the extracted features are also used by the domain classifier to classify whether these features are from the source bridge or target bridge. To make features bridge-invariant, the domain classifier should not predict the extracted feature's source accurately. To keep extracted features damage-informative to various damage states, task predictors should accurately predict damage labels on the source bridge data. Therefore, domain classifiers and feature extractors are trained in an adversarial way which ensures that domain classifier performance is minimized while task predictor performance is maximized in the source bridge. To achieve this adversarial learning, a Gradient Reversal Layer (GRL) is introduced before the domain classifier layer. GRL multiplies the negative constant to the loss function during backpropagation [10].

Further, damage diagnosis consists of multiple tasks, such as localization, detection, and quantification. Due to the distinct performances of various tasks in the source bridge, more learning resources are allocated to extract deeper features for hard tasks. To achieve this, the hierarchical framework is adopted [8] for multiple-task learning. In particular, damage quantification is considered a difficult task due to its performance in the source bridge, and damage detection and localization are considered easy tasks. Once the model is trained, bootstrapping-based mean signals for the target bridge are used to predict the damage information on the bridge.

EVALUATION OF BEVBI ON A SIMULATED VEHICLE-BRIDGE INTERACTION MODEL

In this section, we describe vehicle-bridge interaction data used for our evaluation, the setup for the BeVBI model, and its performance.

Simulated vehicle-bridge interaction data description

The simulated dataset used for the evaluation of our method includes 2 bridge lengths (21 m and 27 m), one-axial oscillator vehicle, and a smooth road profile with no roughness [5]. A simply supported 2-D beam is used to model the bridge. The vehicle is made to run on the bridge several times. In each run, vehicle properties such as speed, the mass of the body, stiffness, and damping of the suspension system are randomly sampled from the given distribution (i.e. normal, uniform). Damage is simulated at the quarter-span or mid-span of the bridge length for each bridge. Further, 3 damage severity level is modeled (no damage, 20%, and 40% beam stiffness reduction) at each damage location). Details of this dataset can be found in [5]. Our subset consists of 2 (bridge length) × 1 (vehicle type) × 1 (road profile) × 2 (damage location) × 3 (damage severity) = 12 (damage scenarios). Further, for each damage scenario, 400 simulation events are used where each simulation event has varying vehicle properties. We used the body as well as the axle vibration signal for the evaluation of our method as both contain information about the bridge's dynamic properties.

Setup for BeVBI model

This subsection describes parameters for bootstrapped signals, the architecture, and hyper-parameters of our unsupervised Domain Adaptation model. Firstly, we spatially interpolate the vibration signal to 640 data points that are chosen empirically such that the signal contains valuable information and is not too big which hinders our unsupervised domain adaptation model learning ability. Then, for each damage scenario, 400 events are divided into N_1= 250 and N_2= 150 training and testing events subsets, respectively. Further, N_{train}= 250 training samples and N_{test}= 150 testing samples were generated by averaging X = 100 randomly sampled events with replacements from training and testing events subsets, respectively. The number, X=100 is empirically determined to best reduce the vehicle property variations. The newly generated samples are normalized based on zero mean and unit standard deviation to help the data-driven model learn faster and lead to better convergence. For our unsupervised domain adaptation algorithm, L2 regularization along with stochastic gradient descent (SGD) is used to avoid overfitting problems during the training [11]. The learning rate is 0.0025 with a batch size of 100. Further, the model was made to run for 300 epochs. We ran the whole experiment 10 times to evaluate the performance of our method. Note that the above-mentioned hyper-parameters are empirically selected.

Performance evaluation of BeVBI on simulated dataset

In this subsection, predicted damage diagnosis results from our method are compared against two baseline methods (MCNN and HierMUD) for damage detection, localization, and quantification tasks [8]. MCNN is a multi-task convolution neural network model that uses source bridge data as a training dataset and target bridge as a testing dataset, while HierMUD uses both source bridge and target bridge data for learning the model. The architecture for both MCNN and HierMUD remains the same as the unsupervised domain adaptation algorithm of our method to avoid any results bias due to architecture complexity. Further, the domain classifier layer is not included in the MCNN, and the bootstrapping-based mean estimation module is not included in either HierMUD or MCNN. The comparison against baselines shows the effectiveness of bootstrapping-based mean estimation as well as unsupervised domain adaptation for diagnosing damage across multiple bridges for varying vehicle properties.

Figure 2 shows the performance of BEVBI against the baseline methods (MCNN and HierMUD) for prediction of damage detection, localization, and quantification for the 27 m bridge (target bridge) and 21 m as source bridge. The results show that our model outperforms the baseline methods by 1.45x in the detection and localization of damage and 1.75x in the quantification of the damage on the target bridge.

t-SNE plots of vibration signal in Figure 3 demonstrate the significance of bootstrapping and unsupervised domain adaptation algorithm in our method [12]. Figure 3(a)

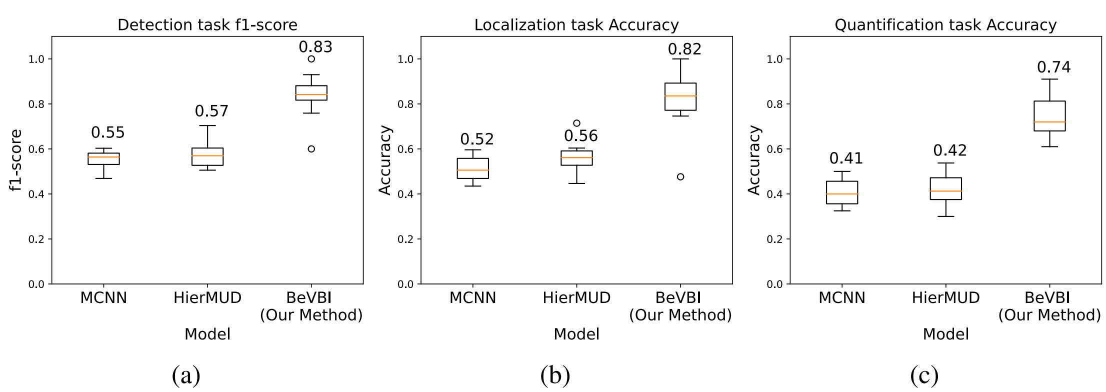
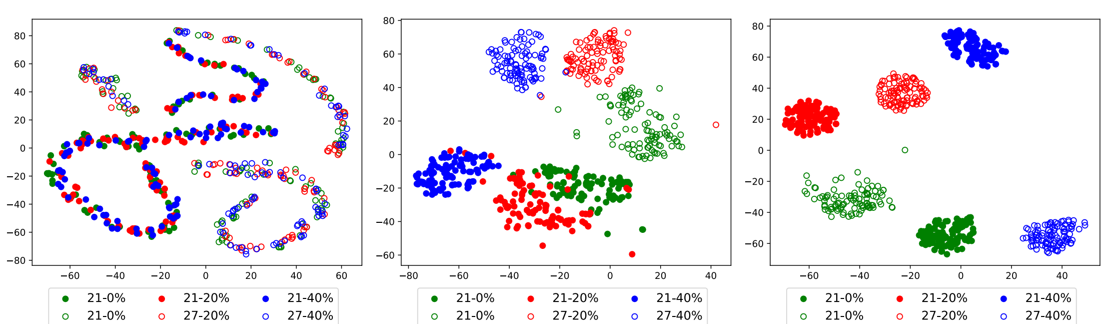


Figure 2. Comaparison between baseline methods and BeVBI for (a) damage detection, (b) damage localization, and (c) damage quantification for 21m as the source bridge and 27m as the target bridge.

shows the t-SNE plot for preprocessed vibration signal at fixed spatial locations. Figure 3(b) shows a t-SNE plot for a bootstrapping-based mean estimated signals. Figure 3(c) shows a t-SNE plot of extracted difficult task features from an unsupervised domain adaptation algorithm. Green, red, and blue markers represent no damage, 20% and 40% damage at the mid-span of the bridge, respectively. Filled and unfilled markers represent 21 m bridge data and 27 m bridge data, respectively. It can be clearly observed from Figure 3(a) that it is hard to separate clusters of different damage states for the same bridge due to varying vehicle properties. Figure 3(b) shows that bootstrapping-based mean estimation reduced the vehicle variation in the vibration signals, and clusters for different damage states for the same bridge are easily separable. However, clusters of the same damage state from different bridges are far from each other as compared to clusters of different damage states from the same bridge. This makes different damage states hard to classify for both bridges. Figure 3(c) shows the UDA algorithm reduces the bridge properties variation and the clusters of the same damage state from both bridges are much closer as compared to clusters from different damage states. In this way, our method is able to diagnose the target bridge in an unsupervised way while being robust to varying vehicle properties.

CONCLUDING REMARKS

In summary, we introduce a Bootstrapping-enhanced Vehicle-Bridge-Invariant approach (BeVBI) for drive-by BHM. Our approach reduces the vehicle variability through bootstrapping and adopts an unsupervised domain adaptation algorithm to predict damage information of a new bridge in an unsupervised way by transferring the diagnosis model learned from another bridge's labeled data. Our approach performs well for monitoring multiple bridges while being robust to varying vehicle properties. It achieves up to 99% accuracy in the detection of damage (mean of 83%), up to 99% accuracy in the localization of damage (mean of 82%), and up to 91% accuracy in the quantification of damage (mean of 74%). It performs 1.45x better in the detection and localization of dam-



(a) (b) (c)

Figure 3. t-SNE embedding plot of various damage states for damage at midspan for 27 m (target bridge) and 21 m (source bridge) using (a) pre-processed vehicle vibration data, (b) bootstrapping-based mean estimated vehicle vibration signal, and (c) task-specific features extracted from the unsupervised domain adaptation model

age and 1.75x better in the quantification of damage as compared to baseline methods without the bootstrapping-based mean estimation or unsupervised domain adaptation.

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