# Damage quantification and localization algorithms for indirect SHM of bridges

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ABSTRACT: This paper presents algorithms for diagnosing the severity and location of damage in a laboratory bridge model. We use signal processing and machine learning approaches to analyze the vibration responses collected both directly from the bridge model and indirectly from a vehicle passing over the model. Features are selected using principal component analysis (PCA), and a regression is performed using the kernel regression method. Various "damage" severities and positions are simulated on a laboratory bridge model by placing additional mass on the bridge. We perform two experiments; one to measure our ability to detect damage severity (i.e. size of the mass), and a second to measure our ability to detect damage location (i.e. position of the mass). In the first experiment, we vary the magnitude of the mass while keeping its location constant. In the second experiment, we vary the location of the mass while keeping its magnitude constant. In both cases, we use a portion of our data to train the algorithm, and another portion to test its validity. We report the accuracy of correctly quantifying the nature of the mass from the test data as a mean square error (MSE).

## 1 INTRODUCTION

With aging infrastructure both in the United States and abroad, structural health monitoring (SHM) for civil applications has become a focus of intense research as a means to objectively determine the condition of a structure.

The American Society of Civil Engineers reports that of the 600,000 bridges within the United States, one in nine bridges is rated as structurally deficient (ASCE 2013). In addition, the recent collapse of the I-5 Bridge in Washington State and the earlier collapse of the I-35 Bridge in Minneapolis demonstrated the need for advanced technologies to monitor bridges. Researchers in the SHM community have already made significant contributions towards developing sensing systems and damage detection algorithms (Doebling et al. 1996, Chang 2011, Frangopol et al. 2010, Casciati and Giordano 2010)

The ultimate goal of SHM is to determine the remaining useful life of the structure. The state of the structure can be determined through a five-step process: (1) existence, (2) localization, (3) type, (4) severity and (5) prognosis of the damage (Rytter 1993).

The vast majority of monitoring systems for bridges require either wired or wireless sensors placed directly on the structure of interest. These techniques have shown some promising results but they require significant capital investment. This paper focuses on an indirect monitoring paradigm where the sensors are placed on a passing vehicle. This indirect approach is more economical; a fleet of vehicles could potentially monitor a large bridge inventory (Lin et al. 2005, Cerda et al. 2010).

Previous work on the indirect monitoring paradigm has examined determining the state of the structure between two (binary classification) or several cases (multiclass classification) (Cerda et al. 2013). Cerda et al simulated damage by adding a 'proxy damage' to a laboratory scale model. In one experiment, they varied the size and location of the proxy damage to measure their ability to determine (2) localization and (4) severity of the damage. They quantified the accuracy using multiclass classification with several discrete classes.

In this paper, we expand on the work of Cerda et al. by performing a regression on a large dataset of proxy damage locations and proxy damage severities, using the same laboratory model as Cerda et al. Using this regression we can determine the

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state of the structure for an infinite number of mass locations and sizes within our training set. To build the regression, we apply principal component analysis to the acceleration signals, and train the kernel regression model by the collected data. This model determines the size and the location of the damage proxy using the MSE as the evaluation score.

## 2 EXPERIMENTAL SETUP AND PROTOCOL

### 2.1 *Experimental setup (Cerda et al. 2013; Wang et al. 2013)*

A general view of the laboratory model used in this project is shown in Figure 1, and schematic of the setup is shown in Figure 2. The model consists of a vehicle that is pulled across the rails by a cable system. The vehicle starts on 'Ramp 1', accelerates up to a constant speed, crosses the middle section, the "bridge," then decelerates on 'Ramp 2.' The vehicle has wired accelerometers so there is a cable rail above to ensure these wires do not interfere with its motion.

The "bridge" is an aluminum plate, 2438 mm (8 feet) long, with two angle beams acting as girders and two rails to guide the vehicle. The vehicle model, as shown in Figure 3, has an independent suspension system. Both the vehicle and the bridge were instrumented with commercial accelerometers. On the vehicle, two sensors are on the sprung portion of the vehicle ('front chassis sensor' and 'rear chassis sensor'), and two sensors are on the unsprung portion of the vehicle, rigidly attached to the wheels ('front wheel sensor' and 'rear wheel sensor'), as shown in Figure 3. One sensor was placed underneath the bridge deck at midspan ('bridge sensor').



Figure 1. The general view of the laboratory setup.

The motors governing the movement of the vehicle and the data-acquisition systems are both controlled by National Instrument's® PXI system running LabView®. By using a single system, we can spatially align the time series data from different runs using the vehicle's position. More details about the experimental setup can be found in (Cerda et al. 2013).
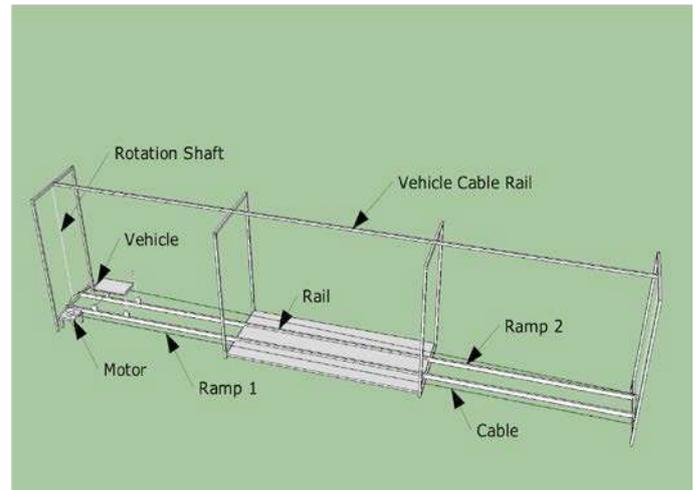


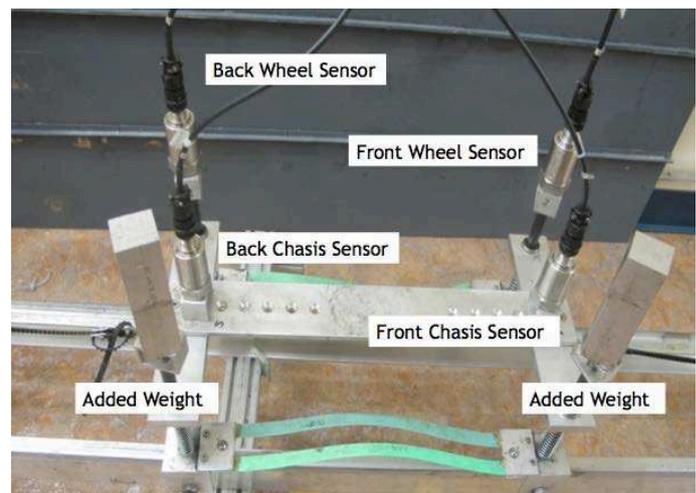Figure 2. The illustration of the laboratory model.



Figure 3. Details of the vehicle.

### 2.2 *Protocol*

In this experiment, the damage proxy is the presence of a mass on the deck. We assume that as the mass level changes gradually, the vibration characteristics will change accordingly. By mapping the relationship between changes in the acceleration signal to changes in the magnitude of the mass, we can determine the state of the bridge from an acceleration signal involving a change in mass size with our training range. The same assumption is applied to the change of the positions.

We assume a heavier mass means more severe damage as it is a more significant change from the baseline condition. In this paper, we use 31 mass levels, with an interval of 5 grams from 0 to 150 grams. We ran the experiments at 2 different speeds. The bridge itself weighs 15.5kg so the added mass

varies from 0%-1% of the mass the bridge. For these severity tests, we have 31 (mass) × 2 (speeds) × 30 (iterations) = 1860 (trials).

To investigate damage localization, a mass of 200 grams was placed at 30 locations, with an interval of 8 cm. We ran the experiment at 4 different speeds. The positions of the mass are shown in Figure 4. In total, for the localization tests, we ran 30 (locations) × 4 (speeds) × 30 (iterations) = 3600 (trials).
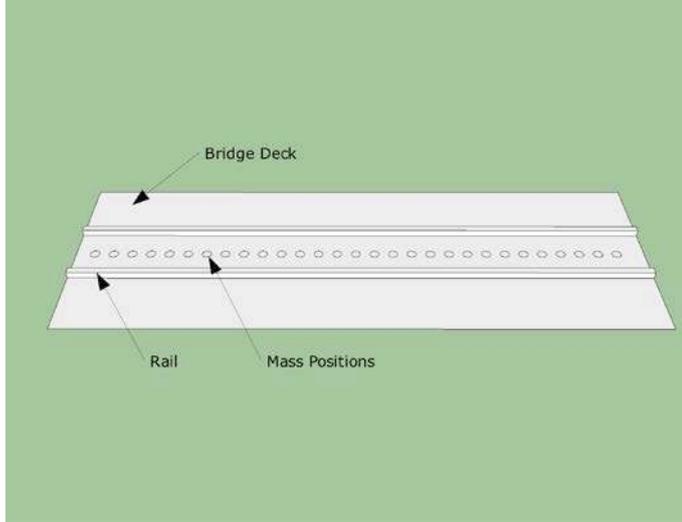


Figure 4. Illustration of mass positions on the deck.

# 3 REGRESSION FOR STRUCTURAL SCENARIOS

## 3.1 *The framework of the signal-processing system*

The goal of our signal processing approach for this experiment was to design a map to associate an acceleration signal with its corresponding bridge condition. In this experiment, we varied the bridge condition in small increments so that we could examine the evolution of the signal as the location or the severity of the proxy damage changed. By mapping this relationship, we were able to record a new acceleration signal of a previously unseen bridge condition, and predict that condition. There are two main challenges: the acceleration signals lie in a high-dimensional space, which is hard to visualize and further model; there is no closed-form formula to describe the relationship between the acceleration signals and the bridge conditions. We solve the first challenge by using PCA to reduce the dimensionality and solve the second one by using kernel regression to build a nonparametric regression model. The signal-processing system thus contains the dimensionality reduction block and the regression block shown in Figure 5.
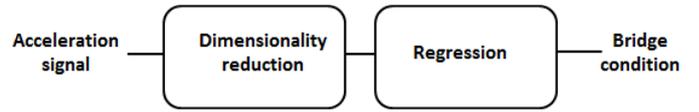


Figure 5. The system of regression for structural scenarios.

## 3.2 *Dimensionality reduction and visualization*

Each acceleration signal is sampled at 1667 Hz, and the vehicle takes roughly 2 seconds to cross the bridge (depending on its speed), it then contains over 3000 signal samples. The high dimensionality leads to the difficulty in visualizing and understanding the distribution of acceleration signals; it is also hard to perform further analysis because of the so-called *curse of dimensionality* (Duda et al. 2000). To solve this, we use PCA (Duda et al. 2000) to reduce the dimensionality. It finds an orthogonal linear transformation from the given dataset and transforms the signals into a new coordinate system such that the first coordinate captures the greatest variance, the second coordinate captures the second greatest variance, and so on. The algorithm to compute PCA is as follows.

$$\bar{x} = 1/m \sum_{i=1}^{m} x_i$$

PCA (extract top k eigenvectors as features):

Given data X={$x_1$, …, $x_n$},

1. Calculate the mean of each column:

$$\bar{x} = (1/m) \sum_{i=1}^{m} x_i .$$

2. Subtract the mean $\bar{x}$ from each vector $x_i$ and get a new matrix **X**.

3. Calculate the covariance matrix $\Sigma$ of X.

4. Calculate eigenvectors and eigenvalues of $\Sigma$ and sort the eigenvectors ascending order based on the corresponding eigenvalues.

5. Select the first k principal components as features.

The implementation details of dimensionality reduction block are as follows: we first take the discrete Fourier transform of each acceleration signal and compute the magnitudes of their frequency spectrums; we then use PCA to analyze the magnitudes of all the acceleration signals. As an example, for visualization, we only preserve the first

three coordinates in Figure 6 to Figure 10. Each subplot is the feature spectrum extracted from the data collected from one position on the vehicle. The colors from red to blue indicate the increasing mass from 0 gram to 150 grams as can be seen on the colorbars. These figures show how the features of the acceleration signals change as the severity of the mass increases. We see a gradual change in the features as the size of the proxy damage increases; we can use these graphs to justify our mapping approach. For a given acceleration signal, we can plot its features in this space, and can deduce the condition of the bridge from the position of the features relative to known cases.
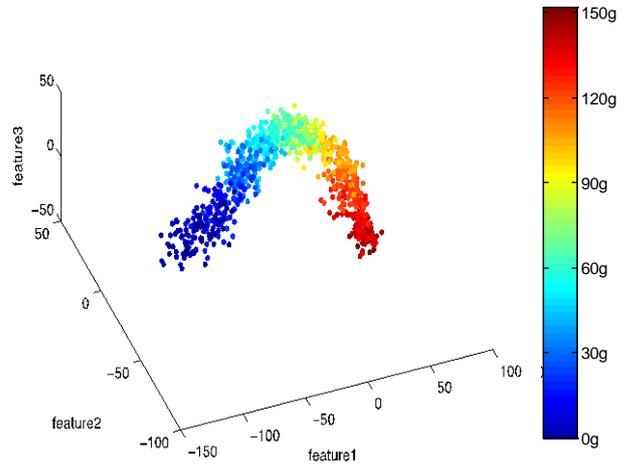


Figure 8. Visualization using first three principal components of the back chassis sensor accelerometer signals.
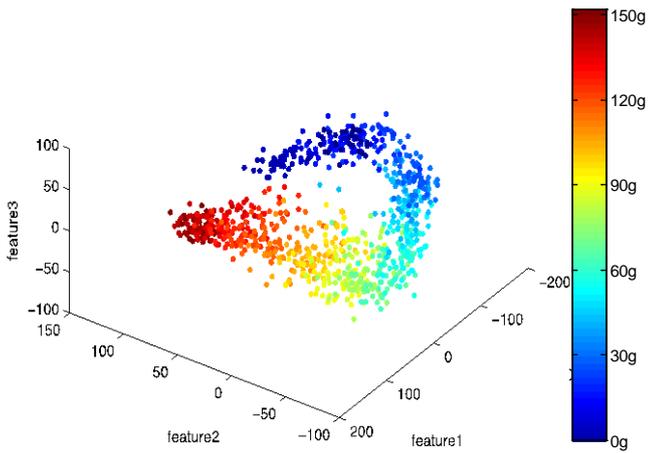


Figure 6. Visualization using first three principal components from bridge sensor accelerometer signals.
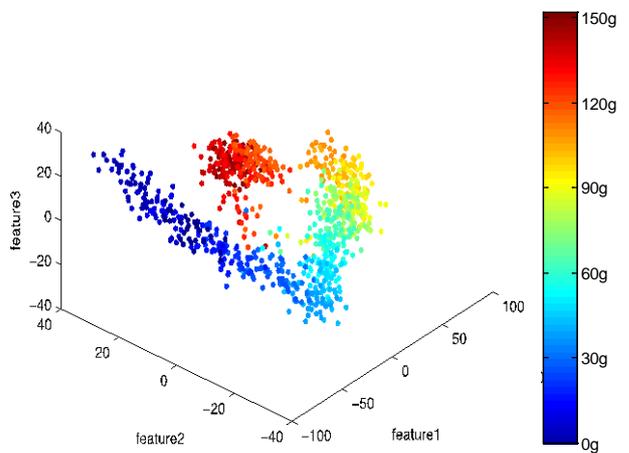


Figure 9. Visualization using first three principal components from front chassis sensor accelerometer signals.
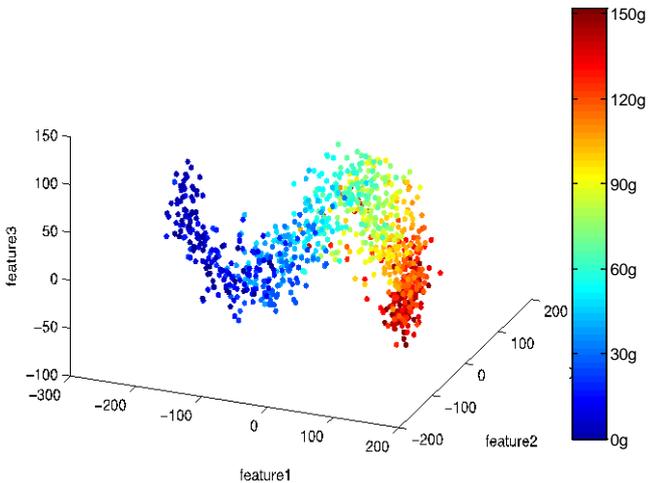


Figure 7. Visualization using three principal components from back wheel sensor accelerometer signals.
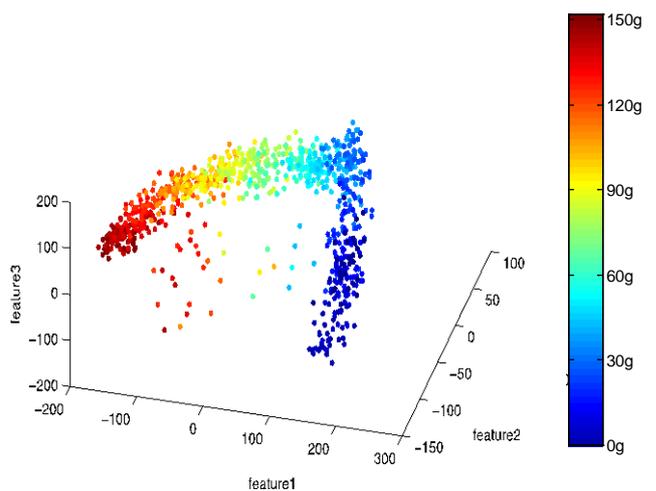


Figure 10. Visualization using three principal components from front wheel sensor accelerometer signals.

## 3.3 *Signal reconstruction for verification*

To verify that using only first three principal components will capture the characteristics of the original data, we reconstruct the signals based only on these principal components. In Figure 11, we demonstrate that the vast majority of the information in the signal is in the first several principal components—the singular values is a measure of information. Figures 12-16 show the reconstruction the signal for each of the sensor. They demonstrate that the characteristics of the vibration, such as peak occurrences, are very close to the original data, which means that to a certain extent, we can represent the original data by the features extracted from the PCA.
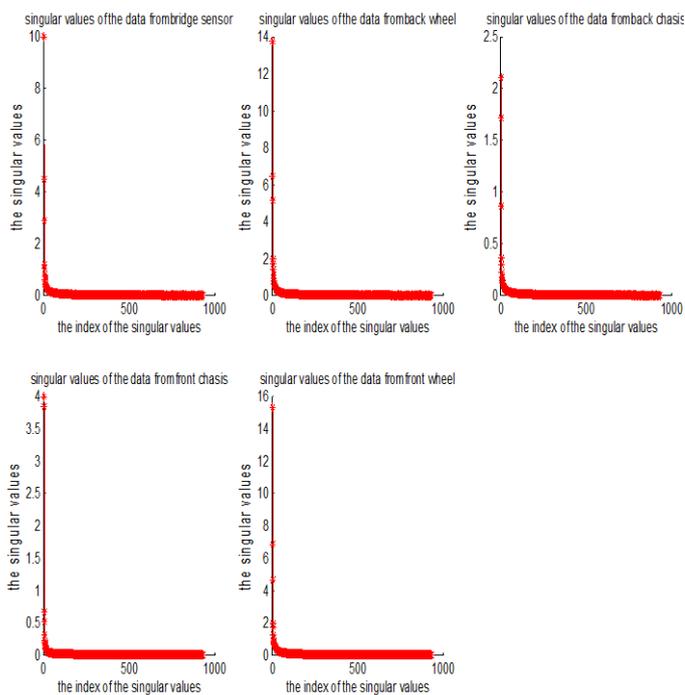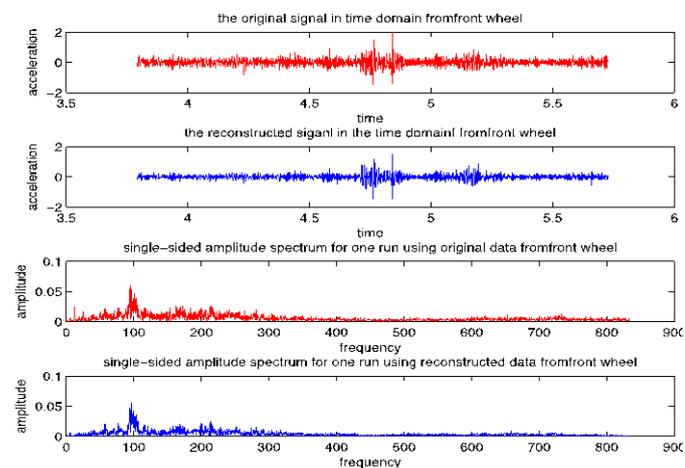


Figure 11. Singular value analysis.



Figure 12. Original and reconstructed signals of the front wheel sensor.
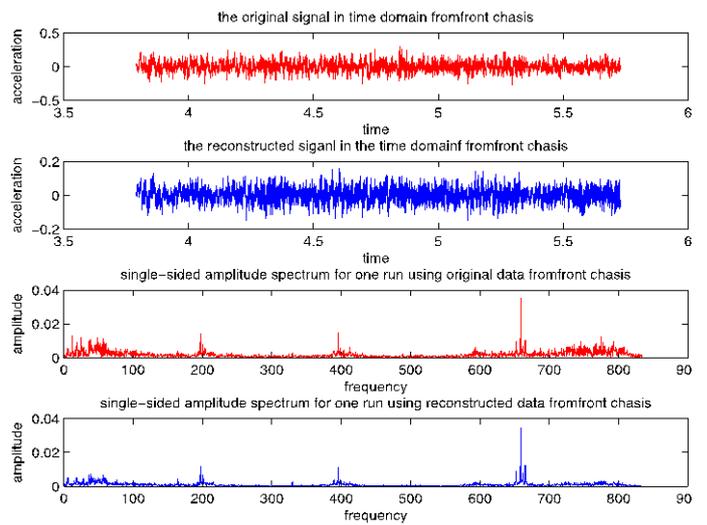


Figure 13. Original and reconstructed signals of the front chassis sensor.
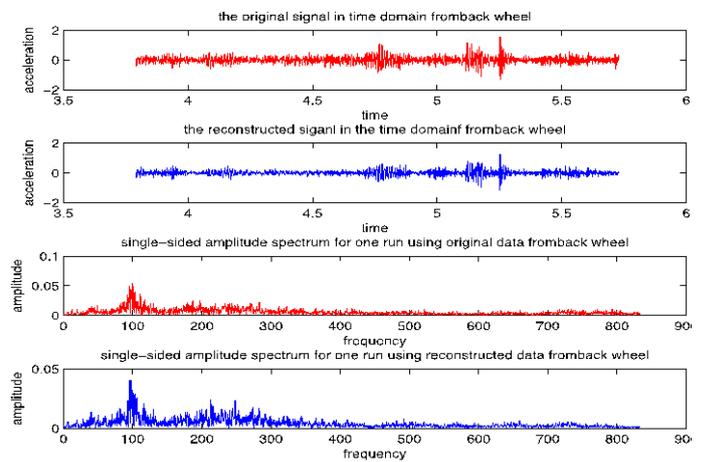


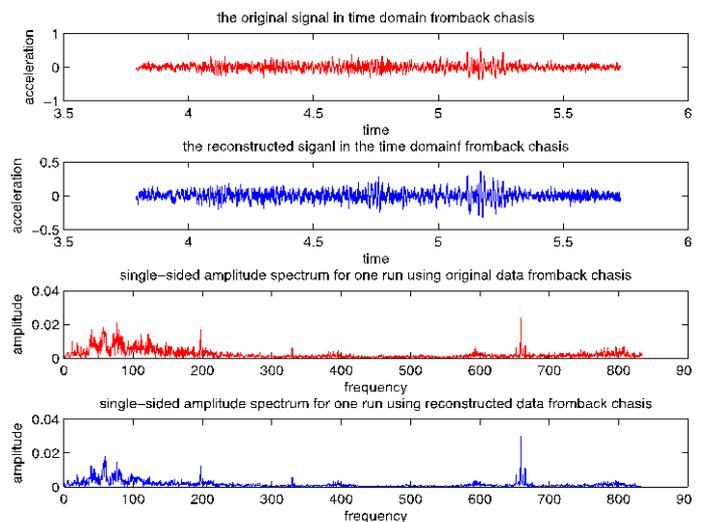Figure 14. Original and reconstructed signals of the back wheel sensor.



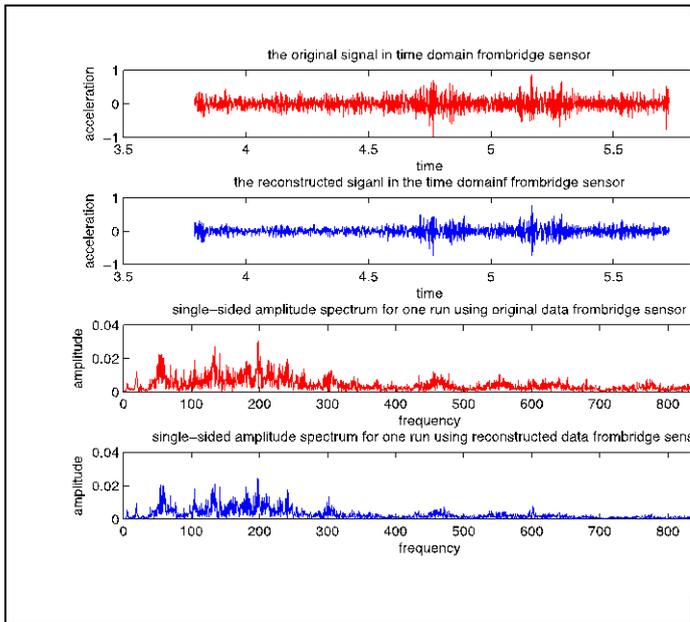Figure 15. Original and reconstructed signals of the back chassis sensor.

Figure 16. Original and reconstructed signals of the bridge sensor.

## 3.4 Regression Model

Regression analysis is an approach that finds possible connections among all the variables and is then used as the means of predicting when a new dataset is presented to the system. Many techniques for regression analysis have been developed. These techniques are categorized as parametric and nonparametric regression (Wasserman 2005). Parametric regression asks for parameters in the model and nonparametric regression relies on the functions that the user chooses, as the basis for data processing.

We use a nonparametric regression analysis method, called kernel regression. After applying PCA, the acceleration signals are represented in a more compact way by using the top three principal components. Based on this, we then look for a relationship between the acceleration signals and the bridge conditions. We train the regression model from the given dataset by using kernel regression (Wasserman 2005). The advantage of kernel regression is that it is a nonparametric method and it finds a nonlinear relationship between a pair of variables by averaging locally. Noh et al. (2012) used kernel regression to define fragility functions for damage classification purposes. Kernel regression works in two phases, the training phase and the testing phase. In the training phase, the inputs of the kernel regression are the first three coordinates of the acceleration signals after applying PCA and their corresponding bridge conditions; the output is the regression model. In the testing phase, the inputs are the unlabeled acceleration signals and the regression model trained previously, and the output is the predicted bridge condition.

**Algorithm** *(Regression for Structural Scenarios )*

*Input:* Labeled training dataset and unlabeled testing dataset.

*Output:* Predicted class labels for the testing dataset.

*Training phase:*

1. Compute the discrete Fourier transform of each signal in the training dataset.
2. Conduct the principal component analysis on the training dataset.
3. Preserve the first three components of each signal and the corresponding eigenvectors.

4. Train a kernel regression model by using the three components of each signal in the training dataset and the corresponding class labels.

*Testing phase:*

1. Compute the discrete Fourier transform of each signal in the testing dataset.
2. Represent signals in the testing dataset by projecting them to the eigenvectors trained in the training phase.
3. Feed the signals into the kernel regression model trained previously and get the predicted class label.

## 4  RESULTS

### 4.1  Regression Testing Protocol

To evaluate our regression system, we perform a series of cross-validation experiments. For each speed and each sensor, we randomly selected 90% of the acceleration signals from all bridge conditions and use them as the training set. The other 10% of the signals form the test set. This random selection is repeated in a 30-fold validation. For each case, we report MSE as the evaluation score.

### 4.2  Severity Results

The goal is to detect the weight changes with different masses put on the bridge through analyzing the acceleration signals. After the model is built, we randomly choose the signals with the mass on the bridge in the range of training data and calculate the

MSE. These results are shown in Figure 17. MSE for each sensor is found at two different speeds. An MSE of zero would denote a perfect regression, and an MSE of 75 (=$30^2/12$) would denote regression that was no better at identifying the size of the mass than a random guess. From the result, we see that signals from the wheel have high MSE error so they are less useful, while the signals from the chassis and the bridge have smaller prediction error.
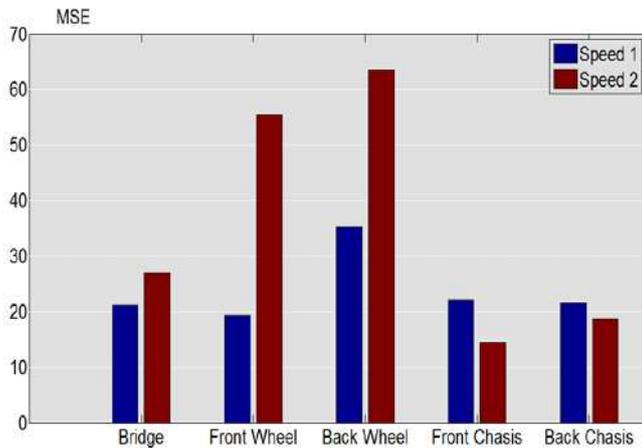


Figure 17. MSE result for the severity regression.

### 4.3 *Localization Results*

The goal here is to find the location of the mass through analyzing the acceleration signals. We randomly choose signals from locations within the training range and calculate the MSE as shown in Figure 18. Again, a perfect regression would have MSE of zero, and a regression that gave a completely random answer would have a MSE error of 80.1 (=$31^2/12$). From the result, it is indicated in the similar way with the location case that signals from the chassis have smaller prediction error than that of the signals from wheels. The MSE for the chassis signals is around 15 on average at different speeds.

### 4.4 *Analysis*

From the above results, we conclude that for the signal processing approach used in this paper, signals from the chassis perform better than signals from the wheels in terms of the prediction error. One possible explanation is the low-pass filtering function of the spring supporting the chassis. As the vehicle is traversing, the spring has the function to filtrate the signal to keep signals with relative low frequencies and filter out signals with relative high frequencies, which associate with noise.

It is also worth noting that the signals from the chassis outperform the signals from the accelerometer located at the midspan of the bridge. This supports our overarching hypothesis that an indirect monitoring approach where sensors are placed on the vehicle may be at least as effective as a direct monitoring approach.
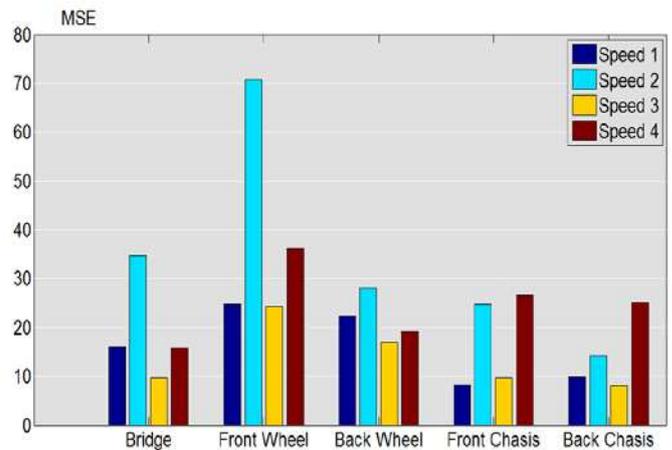


Figure 18. MSE result for the location regression.

## 5 CONCLUSIONS

We present the latest results of our research into indirect structural health monitoring. We expand on our previous work on locating and quantifying damage in a bridge by using the acceleration signal from a passing vehicle. While previous research has looked at several discrete locations or severity levels using multiclass classification, here we build a regression model that can handle an infinite number of possible damage locations and severities within a particular range. We use PCA to reduce the dimensionality of the signal, and kernel regression, a non-parametric approach, to map the signals to the bridge condition. We obtain low errors (quantified by MSE) for all sensors, in particular for chassis sensors. The error for the chassis sensors is lower than the error for the bridge sensor, which indicates that an indirect monitoring approach may be feasible. This work brings us one step closer to providing a bridge diagnosis in an indirect fashion.

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