Bridge monitoring through a hybrid approach leveraging a modal updating technique and an artificial intelligence (AI) method

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Chunhee Cho, University of Hawaii, Manoa

DoSoo Moon, University of Hawaii, Manoa

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16. Abstract

An early damage identification process in bridge structures may offer an opportunity to slowdown progressive failure and thus prevent catastrophic collapses. With a structural health monitoring system which allows real-time measurement of structural responses, early damage in bridge structures can be identified with proper techniques. Recently, data-driven based damage detection has become one of the principal practices. To accommodate the requirement, the project integrates two methods (i.e., a model updating technique and an artificial intelligence (AI) prediction) that can compensate for each other's the weakness that otherwise imposed difficulty in precise real-time application of health monitoring systems. Therefore, this project leverages a mode-updating technique with high-fidelity experimental data to obtain an accurate digital model that represents an actual bridge model. The drawback of the model updating technique (i.e., high computational time) is overcome by applying an artificial intelligence algorithm such as neural networks that are known to be computationally efficient while perusing high accuracy. In this project, a pre-trained convolutional neural network is employed to conduct machine learning for damage prediction. The performances of the proposed method are assessed with various damage scenarios. The prediction accuracy of the network is 97%.

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Table of Contents

About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

Principal Investigator, Co-Principal Investigators, others, conducted this research titled, "Bridge monitoring through a hybrid approach leveraging a modal updating technique and an artificial intelligence (AI) method" at the Department of Civil and Environmental Engineering, College of

Engineering, University of Hawaii, Manoa. The research took place from 08/21/2021 to 08/15/2022 and was funded by a grant from the Pacific Southwest Region University Transportation Center in the amount of $26,649.48. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

Abstract

An early damage identification process in bridge structures may offer an opportunity to slowdown progressive failure and thus prevent catastrophic collapses. With a structural health monitoring system which allows real-time measurement of structural responses, early damage in bridge structures can be identified with proper techniques. Recently, data-driven based damage detection has become one of the principal practices. To accommodate the requirement, the project integrates two methods (i.e., a model updating technique and an artificial intelligence (AI) prediction) that can compensate for each other's the weakness that otherwise imposed difficulty in precise real-time application of health monitoring systems. Therefore, this project leverages a mode-updating technique with high-fidelity experimental data to obtain an accurate digital model that represents an actual bridge model. The drawback of the model updating technique (i.e., high computational time) is overcome by applying an artificial intelligence algorithm such as artificial neural networks that are known to be computationally efficient while perusing high accuracy. In this project, a pre-trained convolutional neural network is employed to conduct machine learning for damage prediction. The performances of the proposed method are assessed with various damage scenarios. The prediction accuracy of the network is 97%.

Keywords: Damage detection, Machine Learning, Structural Health Monitoring

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Executive Summary

An early damage identification process in bridge structures may offer an opportunity to slowdown progressive failure and thus prevent catastrophic collapses. Current manual inspection is labor-intensive, subjective, and unreliable as inspectors are required to visually assess structural members one by one. Thus, reports of bridge inspection are limited with descriptions of visually identifiable information about structures and do not provide fundamental information of their integrity. Furthermore, the cost of labor-intensive manual inspection is high (although the cost of current bridge inspection depends on the bridge size, the price tag runs approximately several thousand dollars for each inspection).

To address these issues, vibration-based damage detection as a structural health monitoring system has become one of the principal practices to prevent structural collapses in civil, mechanical, and other engineering disciplines. These approaches allow real-time measurement of structural responses, this may be possible if proper techniques are employed to identify early damage in bridge structures. Depending on the processing technique, these approaches have two categories: 1) one of the most well-known inverse approaches, the model updating technique, can acquire accurate results by minimizing the difference between a real model and a numerical model; such approach achieves the discrepancies between the pristine and current structure, which indicating the structural damage. However, it requires high computational efforts after the real-time measurement, which is the major limitation in a real-time application. On the contrary, 2) the machine learning (ML) is a representative data-driven solution among the forward approaches. Different from model updating, the ML approach does not have an explicit FEM model. Instead, the ML approach is formulated to predict structural behavior by data pattern. Comparing with model updating approach, ML method establishes entire structural information prior to the on-site real-time measurement, and it allows the delivery of structural damage prediction almost simultaneously right after the measurement. Therefore, the ML model is relatively light and computationally efficient, which enables to predict structural behaviors in a timely manner. Despite the advantage of being simple and efficient, it may suffer from low damage-detecting accuracy if insufficient patterns are used in the ML algorithms. Unfortunately, it is extremely difficult (unrealistic) to obtain data from an actual bridge structure and construct data patterns.

The proposed project integrated two methods (i.e., a model updating technique and a data-driven prediction method) that can compensate for each other’s the weakness that otherwise imposed difficulty in precise real-time application of health monitoring systems. This project leveraged a mode-updating technique with high-fidelity experimental data to obtain an accurate digital model that represents an actual bridge. The drawback of the model updating technique (i.e., high computational time) can be overcome by applying a data-drive method

that is known to be computationally efficient. The proposed approach will then result in a fast and accurate method (i.e., a model-based data-driven method) for early damage identification of bridge structures.

To accurately predict damages with the ML approach, large amounts of structural response data were collected from a series of sensors attached to the structure. Therefore, the damage diagnosis requires high computational efforts. To address such an issue, we suggested a revolutionary approach utilizing an image-based pre-trained convolutional neural network (CNN) to detect bridge damage locations and severities. Our research adopted scalograms which derived from wavelet transform to convert structure dynamic behavior data (i.e. nodal acceleration) into image data (scalogram). Compared with the traditional frequency analysis derived from the Fourier transform, the new method maintains both spatial and temporal information from the original structural behaviors. To generate CNN learning features, six channels of acceleration data are gathered from six strategically selected points of a finite element (FE) bridge model. A pre-trained CNN, Resnet, is adopted to conduct transfer machine learning for higher training efficiency. The performances of the proposed method are assessed with various damage scenarios. The prediction accuracy is 97%

Through the project, our findings are as follows: 1) The proposed method integrated with a sensor-based system enables to continuously monitor structural integrity. As a result, when critical structural elements are damaged, the proposed method clearly informed damage locations (global inspection) and their severity (local inspection). 2) Current biannual inspection may miss the critical and dangerous damage growths before the next inspection cycles. The proposed continuous monitoring timely filled the inspection gap by identifying critical damages before out of control. 3) No additional cost for system improvement is required if a sensing system is already installed on a bridge structure.

Introduction

Among 614,387 bridges in the U.S, almost four in 10 are 50 years or older, and undergo degradation. In addition, 9.1% bridges are currently structurally deficient and functionally obsolete. Despite poor conditions, 188-million trips across structurally deficient bridges are made each day (ASCE, 2017). Although the Federal Highway Administration (FHWA) and the State Department of Transportation (DOT) mandate bridge inspections every two years, they are manually performed, relying on a visual assessment with the naked eye. However, such a process has limitations to assess the structural integrity of a system as visual inspection cannot detect hidden or microscopic damage, which grows over time with progressive consequences. If such damages are not identified at an early stage, as visual inspection may fail to do, protracted damage may lead to expensive repairs or collapse, resulting in a threat to public health and safety.

To mitigate the challenges associated with visual inspection, researchers have studied structural health monitoring for the last few decades. With the advent of sensing technologies, structural health monitoring systems could measure structural responses (Spencer at el., 2004) by collecting and processing data such as acceleration and strain. The processing technique has two categories: the inverse approach and the forward approach. Each approach has pros and cons; one of the most well-known inverse approaches, the model updating technique (Friswell at el., 1995), can acquire accurate results by minimizing the difference between a real model and a numerical model (finite element model (FEM)) by calibrating with high-fidelity experimental test data. This approach has two drawbacks, 1) a high-demand FEM model and 2) complicated optimization processes, which is the major limitation in a real-time application despite high accuracy. Therefore, model updating is a post-processing technique with high accuracy while requiring high computational efforts. On the contrary, a data-driven approach such as an artificial intelligence (AI) method (Sohn at el., 2000) is a representative solution among the forward approaches. This method is highly computationally efficient as it does not rely on a complex FEM model, but only data (more specifically data patterns) from sensors (Cho at el., 2018 and 2019). Despite the advantage of being simple and efficient, it may suffer from low damage-detecting accuracy if insufficient patterns or data are trained with AI algorithms. Unfortunately, it is extremely difficult (unrealistic) to obtain data to show damage cases from an actual bridge structure and construct data patterns.

Although the AI method can be used in real time because of its computational efficiency, its potential problem is low accuracy due to lack of data. To address this issue, the proposed research offers a unique hybrid method by leveraging the benefits of each method, resulting in compensating the disadvantages of each method to conduct structural health monitoring. Through the model updating technique, a real bridge model and a digital model will be synchronized. Such model synchronization enables to generate high fidelity data for AI training. Once the reliable data are obtained, computational efficient AI model was formulated for accurately monitoring bridge structures.

In addition, the proposed approach detours the need for higher mode-shape extractions. To reduce the demand for intensive computing resources from mode shape extraction, scalograms plotted from the wavelet transform will be applied as an alternative feature to illustrate the time history information from acceleration data. A set of scalograms gathered from different locations of the structure will then be consolidated to form ML input features. The scalogram plots graphically present structural response information such as natural frequencies and modes. To decode the structural meanings of the scalogram plots, graphical-based learning algorithms will be applied to the training process. A pre-trained network, Resnet, for damage detection model is adopted to achieve high efficiency and accurate performance.

The scope of this study includes building an accurate FEM model, training data generation, investigation of AI algorithms from the feedback results of laboratory tests, and the validation of monitoring performances.

Technical Background

FEM models and Model Updating

In structural engineering, numerical models are typically formulated by FEMs which physically represent their corresponding structures. FEMs are extensively simulated to estimate responses and predict damage for structures. While the FEMs aim to exactly replicate the behavior of their physical structures, discrepancies are always existed. The discrepancies are created by measurement errors and modeling errors. Measurement errors are related to the sensing equipment and measurement environment, and modeling errors are associated with epistemic uncertainties. However, such modeling errors can be reduced by model updating through adjustment of uncertain FEM parameters and interpreting data from structural dynamic studies.

Model updating refers to the process of parameter estimation for a specific model. When the initial FEM is built, model parameters, such as material properties, section properties, geometry, and boundary conditions, are assumed from basic knowledge. The initial model outputs are based on these input parameters. The updating parameters are decided by measured responses and model outputs. The model updating attempts to minimize the difference between measured data and model-output data, and this is achieved by minimizing an objective function which utilize the measurement and model-output data. In this project, structural natural frequencies and mode shapes are the critical parameters to evaluate bridge damage, therefore, model updating will be engaged to reduce the difference between measured and simulated frequencies and mode shapes.

Machine Learning Approaches

Machine learning (ML), as a branch of artificial intelligence (AI) algorithms, is well known for its high efficiency and accuracy and has been widely used in many fields. ML models have presented strong advantages in structural engineering applications. Especially in damage detection fields (Avci et al., 2021), ML models require less computational efforts while maintaining similar or higher levels of analyzing accuracies compared with traditional approaches such as finite element methods and model updating techniques. The current mainstream ML methods utilize vibration-based structural behaviors as numerical learning features (i.e., natural frequencies and mode shapes). Pawar et al. (2006) developed an artificial neural network (ANN) method for structural damage detection and localization in fixed-fixed beams. Spatial Fourier analysis was utilized to extract mode shapes (learning features) based on the beam-free vibration response. The first three modes were simulated from FE models as learning features and the changes in the modes were considered as damage indicators. Another research was conducted on two simple truss bridges (Mehrjoo et al., 2008) to estimate the damage severities of joints using a back-propagation-based neural network. Natural frequencies and mode shapes of the bridge were extracted as numerical input parameters to the neural network. The study indicated that structural system identification took a large portion of the computational efforts in the entire learning process. Park et al., (2009) introduced a sequential two-phase neural network model using acceleration (time-domain) and mode shapes (frequency domain) to detect the structural damage location and severity, respectively.

Therefore, ML is numerical algorithms that learn and find patterns from data without explicit programming (Fumo, 2018). Based on the cases of data ingestion, there are three types of machine learning: supervised learning, unsupervised learning, and reinforcement learning (Fumo, 2018). Supervised learning is a basic learning type for classification and regression. The algorithm is trained with labeled data and aimed to build a model/function to accurately predict the unknown target of future examples. Unsupervised learning has the advantage of being able to function with unlabeled data. It perceives the input data and generate an abstract algorithm to detect patterns, rules, and summarize and cluster the dataset to exhibits high proximity. Reinforcement learning is an algorithm or model that learns from mistakes and get improvement upon new situations using trial-and-error method. Therefore, based on the proposed application, supervised learning with deep learning architecture is utilized in this project.

A deep learning algorithm (or deep neural network (DNN)) is composed of neurons which are typically organized into multiple layers. Each neuron has inputs and produces a single output which is sent to multiple other neurons. Neurons of one layer connect to neurons in the following layer, and each connection is assigned a weight that represents its relative importance (Dertat, 2018). A general DNN is structured with input, hidden, and output layers. The input layer is a data-receiving interface that captures learning examples. The formulation of hidden layers varies based on the functionality of the network. In our research, the hidden layers are configured with several fully connected layers associated with network dropout, activation layers, group normalization layers and a regression layer. An output layer is located on the end of the network to display prediction results from the regression. In general, these layers in DNN are stacked sequentially (Brownlee, 2019) and each layer performs different functions to achieve ultimate goals.

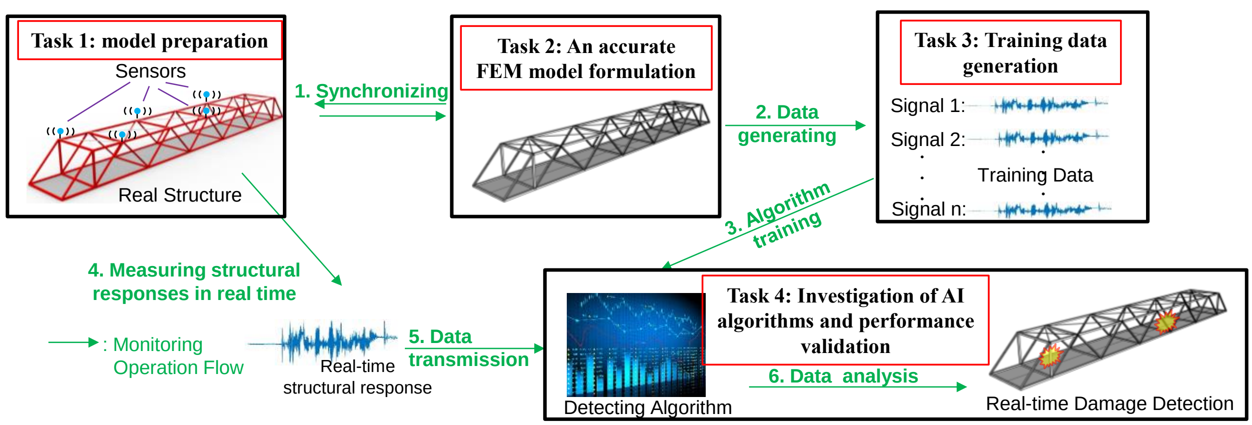
Research Development

Methodology

The proposed research is a hybrid method to integrate an AI model with data generation from a model updating technique. The hybrid approach realizes a real-time application of structural health monitoring by establishing entire structural information in ML prior to the on-site real-time measurement, and it allows the trained ML network to produce the damage prediction simultaneously. The monitoring operation flow of the proposed method with essential research progresses (Figure 1) is as follows:

1. Model synchronization: using the model updating technique, a real structure and a FEM model are synchronized to obtain an accurate numerical model.
2. Various data generation from the accurate model: with the aid of the accurate model, various extreme scenarios are simulated to extract structural responses (AI training data).
3. AI algorithm train: the data is extracted and transformed feature for AI training.
4. Real structural response measurements from sensors: through a sensing system, real-time structural responses are measured.
5. Data transmission: the captured data is transferred to the developed AI algorithm.
6. Data analysis for early damage detection: the trained AI will decide damage location and its severity.

Figure 1. Hybrid approach for a real-time application of structural health monitoring

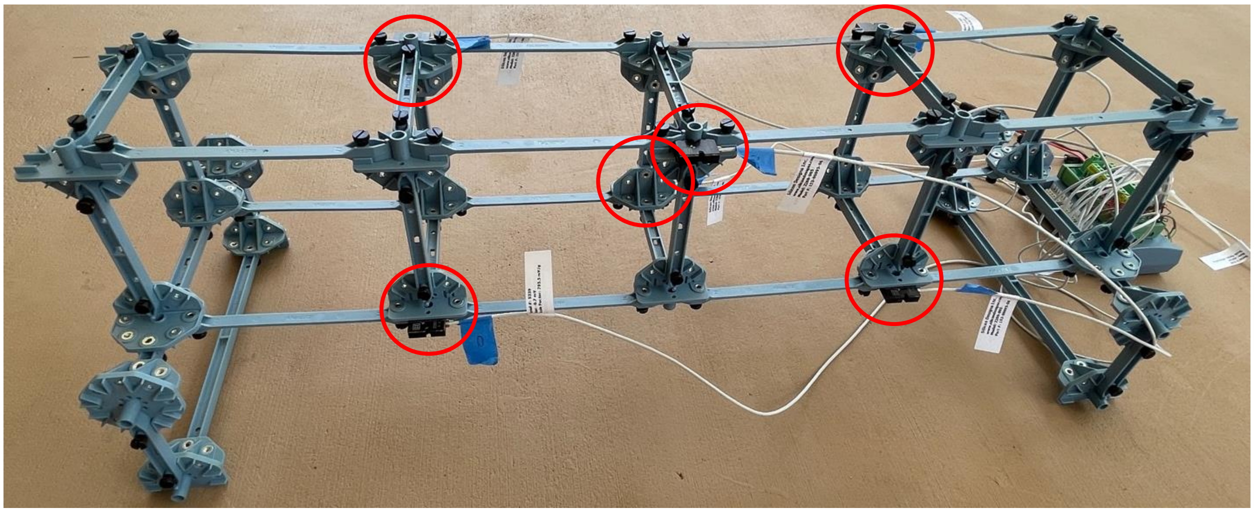


Project Task Arrangements and Deliverables

Task 1. Preparation of project development

Task 1 pertains to a laboratory experimental setup for use in system development. To facilitate project development, the research team established a laboratory experimental setup by building a miniature frame-bridge model as shown in Figure 2.

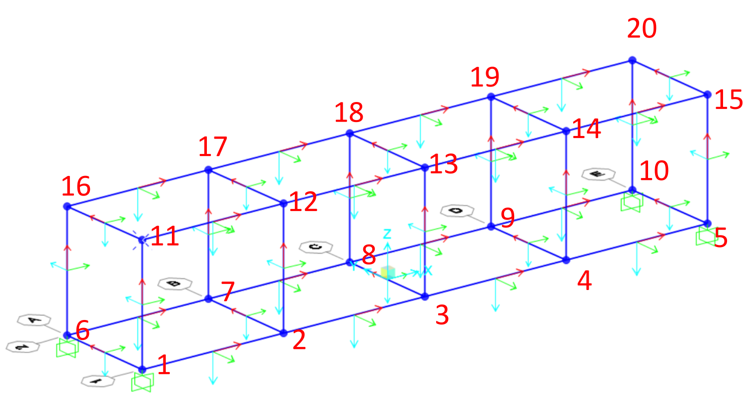
Figure 2. Miniature Frame Bridge Model with Six Accelerometers Attached



The four-bay bridge model is composed of 20 nodes and 36 frame members. On each bay of the bridge, there are four horizontal flat members with a length of 180mm, making 720mm in total length. The joints from the lower and upper levels are connected with I-shape beam members and the two sides of the bridge are parallel attached through I-shape beam members, making the bridge’s total height and width 125mm and 105mm, respectively. The material properties and section properties will be introduced in the model updating section. In the meanwhile, to create a comprehensive representation of the proposed method, a numerical FE model is built using OpenSees software as shown in Figure 3.

Accelerometers (Model 2260 1-Axis Module from Silicon Designs, Inc.) are strategically deployed on the bridge model for acquisition of dynamic structural responses (as circled in Figure 2). In detail, six accelerometers are attached diagonally along two sides of the bridge measuring nodal acceleration data. In the numerical model, the data from the corresponding nodes (node 2, 4, 8, 13,17, and 19) are collected.

Figure 3. Numerical representation of bridge model



Task 2. An accurate FEM model formulation by the model updating technique

This task pertains to formulating an accurate FEM model that can generate reliable training data (e.g., various data patterns) for the data-driven method. To begin with, dynamic properties of the laboratory bridge model, such as natural frequencies and mode vectors, will be extracted by the peak-picking method or the eigensystem realization algorithm. Then, an FEM model is built with the same dimensions and material properties of the miniature bridge model. Although this FEM model is built following the same design specification as the miniature model, dynamic properties of the FEM model are expected to be deviated from those of experimental results due to the inherent differences in nominal material properties, ideal boundary conditions, fixed damping ratio, etc. To minimize discrepancies between the actual and FEM models, we formulated an optimization problem as shown in Eq.1. Through continuous iterations in the optimization process, the FEM model was optimized to match the actual model.

$$\min_{K} \sum_{i=1}^{n} \left\{ \left(\frac{\lambda_i^{EXP} - \lambda_i(K)}{\lambda_i^{EXP}} w_1 \right)^2 + \left(\frac{1 - \sqrt{MAC_i(K)}}{\sqrt{MAC_i(K)}} w_2 \right)^2 \right\} \tag{1}$$

$$\text{subject to } K_L \leq K \leq K_U$$

where K is the stiffness matrix extracted from the FEM model; i denotes the mode number; n is the total mode number (generally considered up to 90% mass participation); $\lambda_i^{EXP}$is the eigenvalue at the i^{th} mode extracted from experiment; $\lambda_i(K)$ is the eigenvalue at the i^{th} mode calculated from the FEM model when the stiffness matrix is K; w_1 and w_2 are weighting factors; K_L and K_U are lower and upper bounds of K matrix, respectively. The lower and upper bounds will be decided based upon the material properties of the system, and the allowable variances.

In the equation, $\mathrm{MAC}_i(K)$ represents the modal assurance criterion between the *i*-th experimental and simulated mode shapes/eigenvectors at measured DOFs, i.e. $\boldsymbol{\psi}_i^{\mathrm{EXP,m}}$ and $\boldsymbol{\psi}_i^{\mathrm{m}}(K)$.

$$\mathrm{MAC}_i(K) = \frac{\left(\left(\boldsymbol{\psi}_i^{\mathrm{EXP,m}} \right)^{\mathrm{T}} \boldsymbol{\psi}_i^{\mathrm{m}}(K) \right)^2}{\left\| \boldsymbol{\psi}_i^{\mathrm{EXP,m}} \right\|_2^2 \left\| \boldsymbol{\psi}_i^{\mathrm{m}}(K) \right\|_2^2}, i = 1 \ldots n_{\mathrm{modes}} \tag{0}$$

Here $\|\cdot\|_2$ denotes the $\mathcal{L}_2$-norm of a vector. Ranging from 0 to 1, the MAC value represents the similarity between two vectors. When two vectors are collinear, the MAC value is close to 1. When two vectors are orthogonal, the MAC value is close to 0.

For this optimization procedure, a multi-start approach is conducted in order to find possible global minimum. By solving the optimization problem, we obtained the accurate FEM model that emulates real structural responses. In the meantime, the updating procedure is separated into 3 steps (as shown in Figure 4). The multi-step model updating simplifies the computation demands of model updating, and it accommodates the requirement of different analysis method from the numerical model and the bridge model. The first step is to update the natural frequencies by conducting eigen analysis in numerical model, and the frequency responses from bridge model are derived from peak-picking method (in frequency domain). After the bridge frequencies are matched in step 1, mode shapes are being updated by performing transient analysis in the numerical model; an imposed load is applied to the bridge model to gather bridge acceleration data. The measured acceleration data is processed into frequency domain information through Fourier transform. Afterwards, the normalized mode shapes are updated in step 2. At the end, in step 3, a random horizontal bridge member is replaced by a 3D printed bridge member (Figure 5 and Figure 6) to emulate a damage scenario for final model updating. From Figure 6, two flat beams with two different thicknesses are printed representing moderate and severe damage. In the numerical model, a member stiffness degradation percentage is assumed to classify damage severity (100%-90% degradations, 89%-50% degradations and 49%-10% are considered as undamaged, moderate damaged and severe damaged structure, respectively). All the updating parameters and targets are listed in Table 1.

Figure 4. Model Updating Procedure Chart

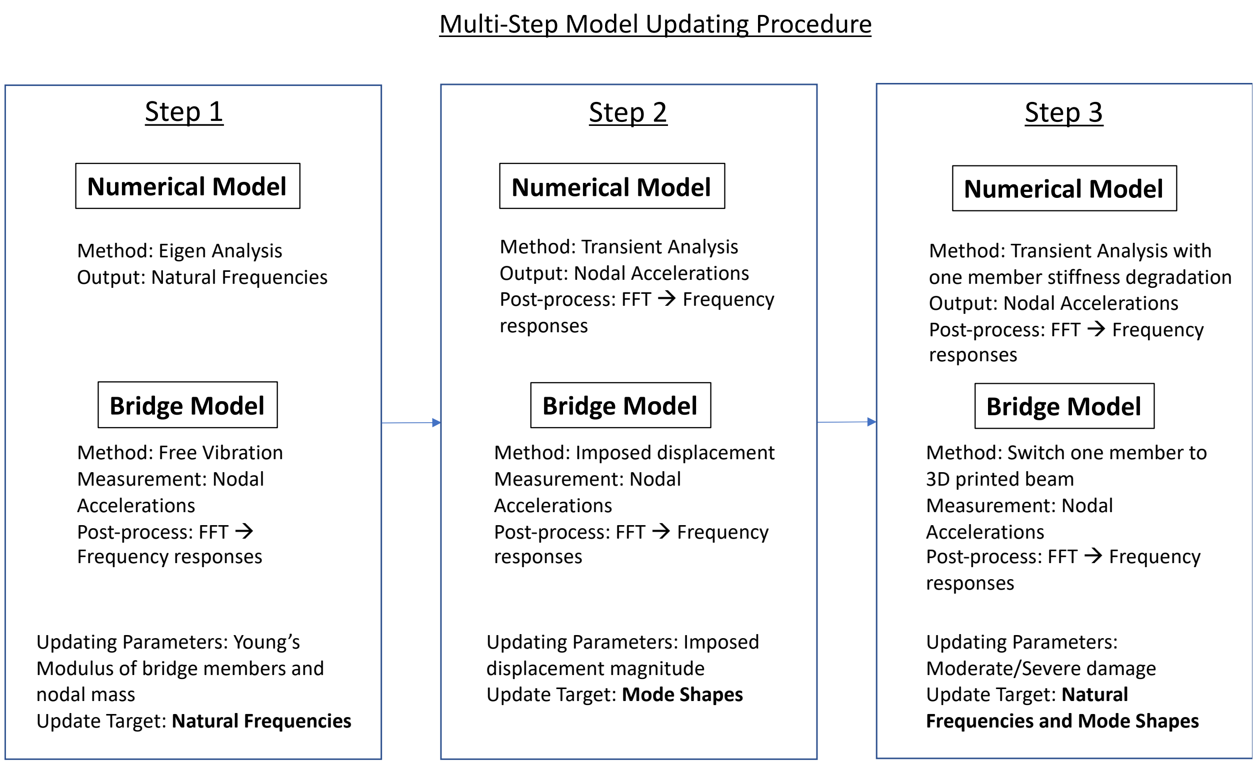


Table 1. Model Updating Parameters and Targets

	Updating Parameters			Update Targets			
	Parameters	**Initial Values**	**Updated Values**		**Bridge Model**	**Numerical Model**	**Errors**
Step 1	Young's Modulus	2,300 MPA	2,345 MPa	1st Frequency	8.8 Hz	8.8 Hz	0%
	Nodal Mass	33 grams	34 grams	2nd Frequency	16.4 Hz	15.8 Hz	-3.7%

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Step 2	Free Vibration Excitation	Unit load	1.1 x Unit load	1^{st} Mode Shape at node 13	0.723	0.715	1%
Step 3	Bridge Member Stiffness	Moderate/Severe Damage	Moderate/Severe Damage	N/A	Thin Member	10%-49% Stiffness	N/A
				N/A	Thick Member	50%-89% Stiffness	N/A

Figure 5. Bridge Model with One Damaged Member

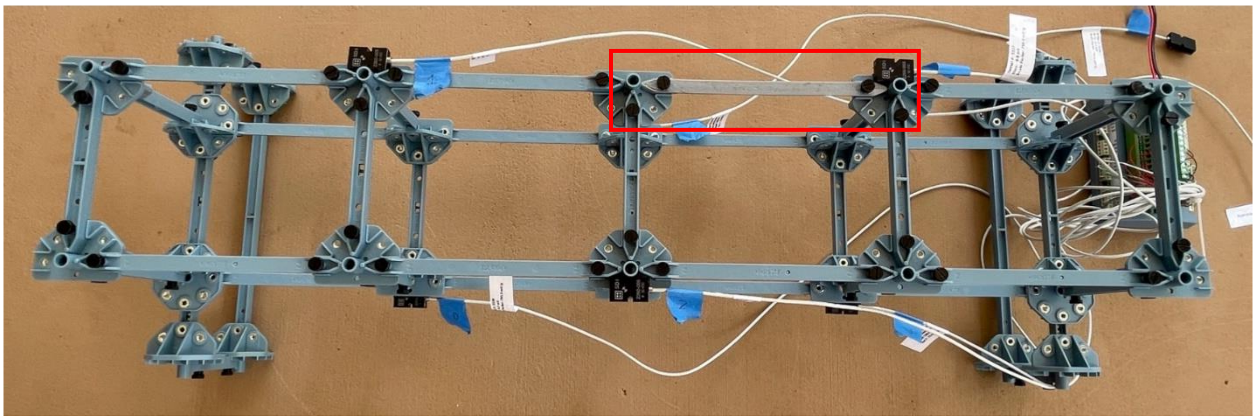


Figure 6. Bridge Members: Original, Moderate Damage and Severe Damage Member (from left to right)

Task 3. Data generation for training an algorithm of the data-driven method

After the accurate FEM model was obtained from Task 2, the research team designed and simulated various damage scenarios by adjusting properties of structural elements in the numerical model.

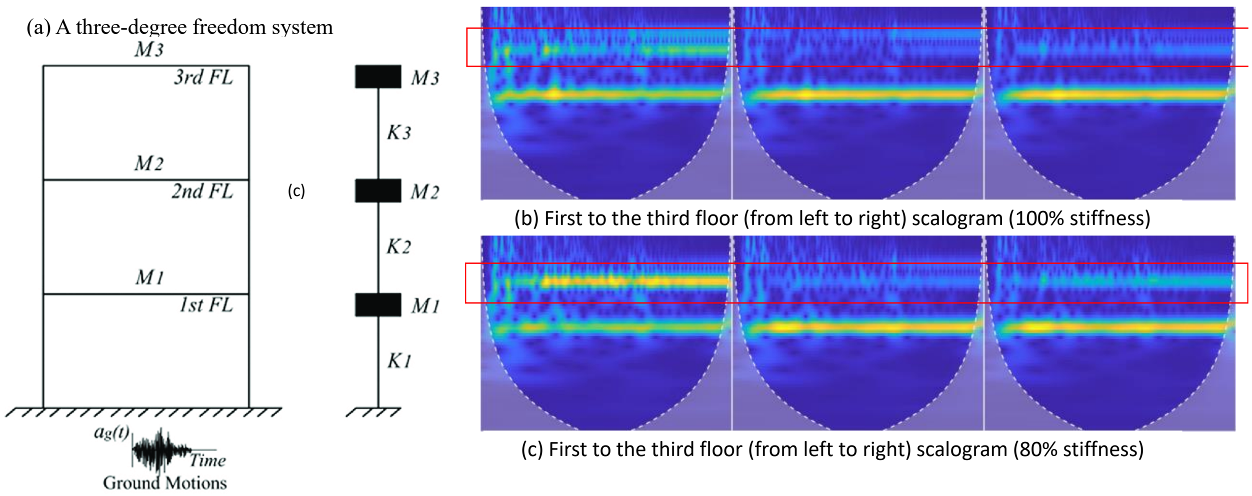
In order to generate ML training examples, fast Fourier transform (FFT) can be the one of most common time-frequency analysis methods for feature extraction in ML based damage detection. The changes of frequencies can reflect structural degradation; however, there is no time related details including damping effects are preserved. To address this issue, a wavelet transform was applied in this project.

Wavelet transform – scalogram

Compared with the FFT approach, the wavelet transform not only presents the signal frequencies magnitude but also shows where the signal has changed. The acceleration data can be converted into wavelet form data, and the visualized plot is called a scalogram. The scalograms contain both frequency and time information.

Figure 7 shows an example of the wavelet transform. For the pilot study model, a three-story building is modeled, and three channels of acceleration data subjected to a ground excitation are measured. The acceleration is converted to 2-D scalograms, and these scalograms will be stitched as a training image feature. The structural damage is simulated through member stiffness loss. Figure 7 shows two sets of scalograms with non-damaged and damaged conditions for the system. Comparing Figure 7 (a) and (b), it is observable that the second frequency bars (in red rectangular frames) have significantly changed due to the stiffness degradation of the first-floor column (80% of undamaged stiffness). From this finding, the structure damages can be presented by the changes in scalograms. Different structure damage locations and severities will appear differently in scalograms. When comparing specific location scalograms with one another, the change in intensity and magnitude represent a change in mode shape and frequency. However, interpreting and summarizing such differences are difficult; therefore, machine learning is more effective in identifying these differences since machine learning can review large volumes of data and discover specific trends and patterns that would not be apparent to humans (Asquero, 2022).

Figure 7. Scalograms As Damage Detection Machine Learning Features



(b) First to the third floor (from left to right) scalogram (100% stiffness)

(c) First to the third floor (from left to right) scalogram (80% stiffness)

Bridge learning example generation

To emulate the structural damages, the changes in member stiffness are simulated in FE analysis. Single-member damage scenarios are considered in this project. To verify the training process efficiently, the damages from horizontal bridge members are considered.

In the real practice, it is very difficult to predict the deterministic values (particular percentage of stiffness) of a damaged member thru regression, since the tiny change (i.e. 1% stiffness loss) cannot make noticeable changes in frequencies and mode shapes. Therefore, in this project, the stiffness degradations will be labeled into three groups (undamaged, moderate damages and severe damages) for classification ML training. Furthermore, in the real practice, such health monitoring or damage detection is for screening the potential damages occurring on the structures (moderate for non-urgent repair, and severe for urgent repair/demolish, etc.), therefore, it is more practical to generate an evaluation standard, such as undamaged, slightly damaged, moderate damaged and severe damaged. It can be customized based upon different requirements and labeled differently for various projects.

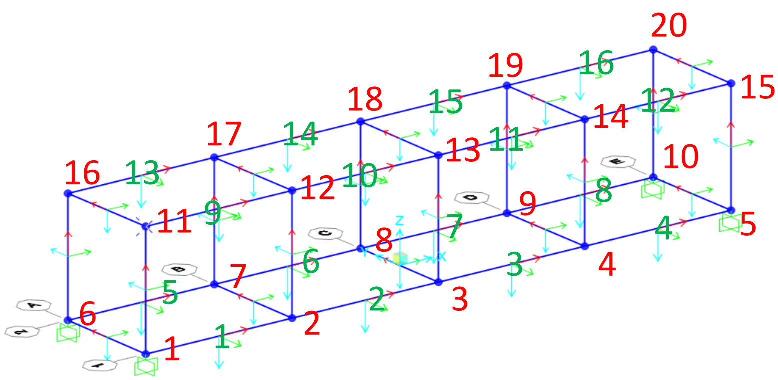
Therefore, there are in total 16 members with undamaged, moderate, and severe damaged scenarios in the study. Table 2 lists the classification attributes and labels. The frame member damage cases are categorized into three levels: undamaged (100%-90%), moderate damage (89%-50%), and severe damage (49%-10%). A 2% stiffness degradation interval is applied for each damage level to generate distinctive learning examples. A total of 688 machine learning examples are created using this method. All the member arrangements are demonstrated in Figure 8.

Table 2. Damage Classification Examples and Learning Label

Bridge Member	Damage Level	Stiffness degradation percentage	Number of examples	Learning Label

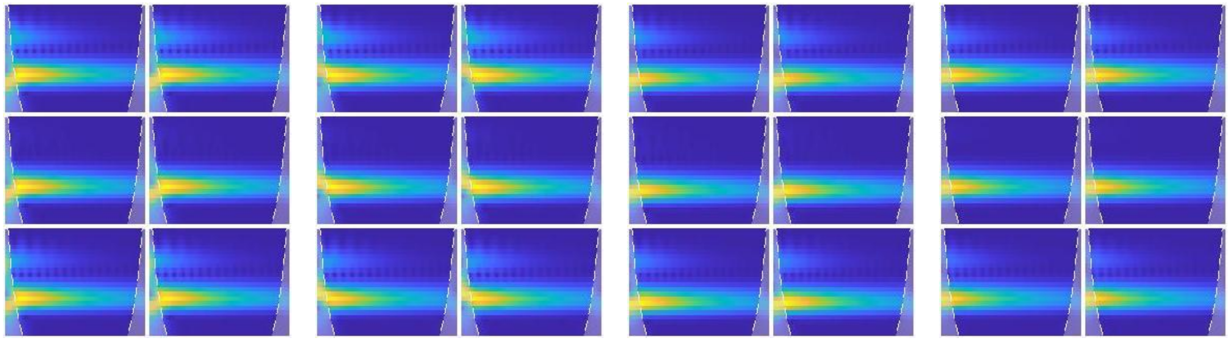
1-16	Undamaged	100%-90%	48	E-U
	Moderate damaged	89%-50%	320	E1-M to E16-M
	Severe damaged	49%-10%	320	E1-S to E16-S

Figure 8. Bridge horizontal member arrangements



To generate learning features, acceleration data subjected to a random external excitation from selected joints are recorded from a numerical model or a real model. In this project, six acceleration data from nodes 2, 4, 8,13,17, and 19 are collected by running the OpenSees simulation. From the node data, six scalograms converted through the wavelet transform are stitched into one image to serve as a learning feature (Figure 9). The order of the six scalograms are: node 2 and node 17 is in the first row (from left to right), node 8 and node 13 are in the second row (from left to right), and node 4 and node 19 are in the third row (from left to right). Figure 9 illustrates four different damage cases: (a) indicates moderate damage in member 12; (b) shows severe damage in member 12; (c) plots another severe damage occurs in member 11; (d) represents an undamaged case.

Figure 9. Scalograms Generated in Numerical Model as Machine Learning Input Features



(a) Moderate damage in member 2 (b) Severe damage in member 2 (c) Severe damage in member 12 (d) Undamaged

Task 4. Investigation of AI algorithms and data patterns for damage detection

The proposed method adopts the data-driven method to monitor structural health by investigating structural integrity from structural response data (and patterns) in a real-time manner; therefore, accurate but fast identification of data patterns in relation to structural responses is the key to success of this research. Since the formulated data form is a series of patterns, Task 4 explored deep-learning algorithms (based on an artificial neural network) that are well known for high performance in pattern recognition with high computing efficiency. Iterative improvement will be made to the deep-learning algorithms (more specifically parameters of the learning algorithm) with experimental testing on the miniature model; this step will include extensive algorithm investigation and exploration of data forms to improve accuracy of damage detecting ratio in bridges structures. Finally, experimental validation will be conducted in a real time manner.

Transfer learning and pre-trained models

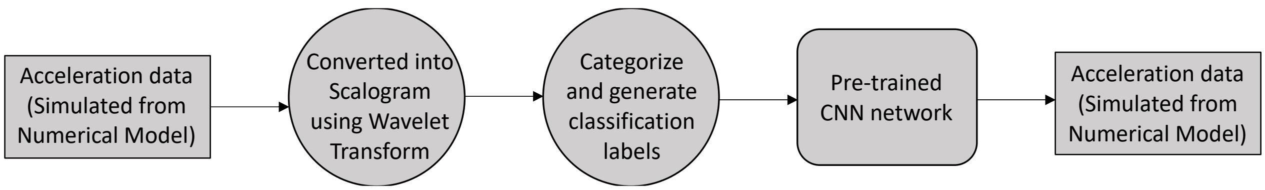
Lately, among various types of machine learning technologies, deep learning is gaining much popularity due to its supremacy in terms of accuracy when trained with a vast amount of data (Mahapatra, 2019). With the expansion of computer vision, image-based deep learning models have been rapidly developed. These models are trained using a substantial visual database and are initially applied toward object recognition (Krizhevsky et al., 2017). Although the input training image types and classes of these models are different from the images in this study, the architecture and layer knowledge of these models can still be adopted to eliminate the initial training cost. Therefore, to achieve high training efficiency and accuracy, this study is conducted based on transfer learning.

Transfer learning is a subfield of machine learning which applies the previous achievements to a different but similar task (Brownlee, 2019). With the knowledge from a related task that has already been learned, learning efficiency in a new task will be significantly improved. Usually, transfer learning uses a pre-trained model that is created and trained by a group of researchers or a well-established institute with an extremely large dataset. Currently, transfer learning has been commonly used for computer vision; such as visual recognition, image captioning, and object classification (Sarkar, 2018). There is a wide range of pre-trained models, especially some are winners of ImageNet (Fei-Fei et al., 2010) classification benchmarks (ImageNet, 2021), such as AlexNet, VGG, GoogLeNet, and Resnet, in chronological order. Among these models, a comprehensive model (Resnet) is selected in this study.

Learning procedure and Results

The 688 learning examples are randomly separated into 95% training examples (654) and 5% testing examples (34). Figure 10 demonstrates the transfer learning process. First, acceleration data from 6 nodes of the bridge is recorded for all damage scenarios. Second, scalograms are categorized into groups with different labels accordingly. Third, all the training examples are inputted into pre-trained networks for transform learning to reach 100% prediction accuracy. Finally, the testing examples are predicted with damage location and severity for performance evaluation.

Figure 10. Learning Procedure Flowchart



For this study, the efficiency of the pre-trained network is tested. To accommodate the classification requirement, the last fully connected layer is modified to fit 33 classes (labels). The prior learned knowledge from Resnet is preserved in the transfer learning process.

Stochastic gradient descent with momentum (SGDM) optimization algorithm is selected through a trial-and-error method. The other optimizers considered are adaptive moment estimation (Adam) and root mean square propagation (RMSProp). Stochastic gradient descent updates the network parameters (weight and biases) to minimize the loss function (cross-entropy, shown in Eq.3) by taking small steps at each iteration in the direction of the negative gradient of the loss (Brownlee, 2021). Momentum helps accelerate the gradient descent and it helps with faster convergence. Eq. 2 and 3 demonstrated the SGDM optimizer (Khandelwal, 2021).

$$\min \quad Loss = -\sum_{c=1}^{N} y_c \, log(p_c) \qquad (3)$$

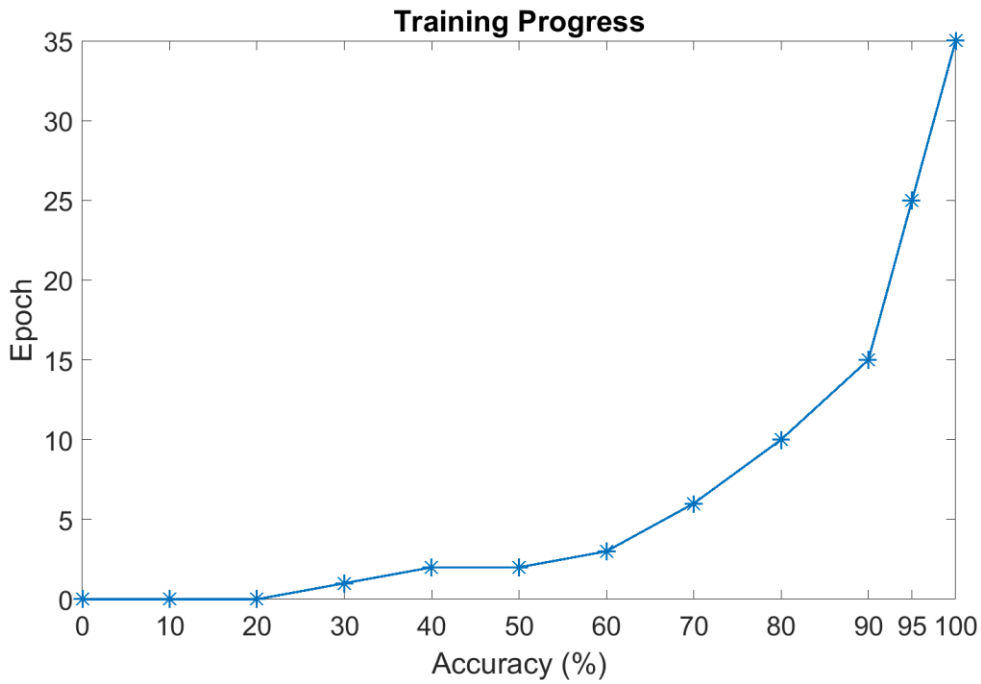
where N is the number of prediction class, y_c is the indicator for each class, and p_c is the predicted probability.

$$\begin{aligned} &\theta_{l+1} = \theta_l - \alpha\nabla(\theta_l) + \gamma(\theta_l - \theta_{l-1}) \\ &until \ \|\theta_l - \theta_{l-1}\| < 10^{-10} \end{aligned} \qquad (4)$$

where θ is the weight parameter; α is the learning rate; ∇ is the gradient operator; γ is the moment term which takes gradient of previous time steps into consideration.

Since the network is trained with prior knowledge (weights and bias parameters), the training accuracies gained rapidly after the first epoch. Since Resnet has an advanced network architecture, the accuracy ascends to 30% in the first epoch. To achieve 100% training accuracy, a total of 35 epochs was required. Figure 11 summarizes the training progress.

Figure 11. ML Training Progress

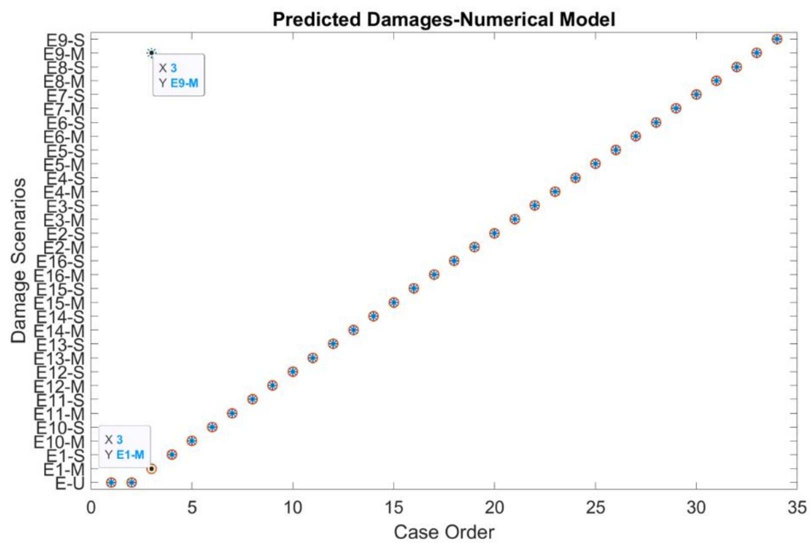


Eq.5 calculates the prediction accuracy percentage. The accuracy is defined as number of correctly predicted label over the total number of labels.

$$Accuracy\ (\%) = \frac{No.of\ correctly\ predicted\ labels}{Total\ No.of\ labels} \times 100\% \qquad (5)$$

The testing results of Resnet model are shown in Figure 12 which includes one wrong prediction case. The mis-predicted case is: Member 1 moderate damage is predicted to be member 9 moderate damage. The estimated prediction accuracy is 97%.

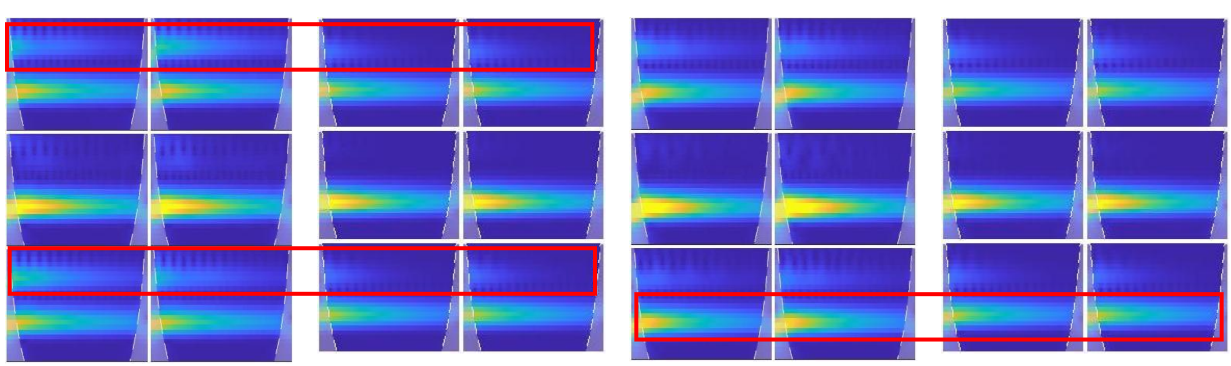
Figure 12. Predicted Damage Scenarios - Numerical Model



Experimental Validation

To validate the proposed approach, four randomly selected damage scenarios are imposed in the bridge model with two sizes of 3D printed flat beam (as shown in Figure 5 and Figure 6). They are: member 1 with severe damage (labeled as E1-S), member 11 with severe damage (labeled as E11-S), member 12 with moderate damage (labeled as E12-M), member 12 with moderate damage (labeled as E14-M) and undamaged (labeled as E-U). Figure 13 illustrates a comparison between measured structural behavior and simulated model output of E-U and E14-M cases. In Figure 13 (a) and (b), undamaged bridge scalograms are plotted, measured case and simulated case appears similar first mode trend (the brightest bar in the plot). The discrepancies occur at the second mode (in red rectangular frames), which measured case shows slightly higher magnitude. In Figure 13 (c) and (d), measured case appears higher first mode magnitude in node 4 and node 19 (in red rectangular frames). However, expect these differences, most features are preserved from measured data.

Figure 13. Scalogram Comparison Between Bridge Model and Numerical Model



(a) Measured Undamaged Bridge (E-U)	(b) Simulated Undamaged Model	(c) Measured Member 14 moderate (E12-M)	(d) Simulated Member 14 moderate damage

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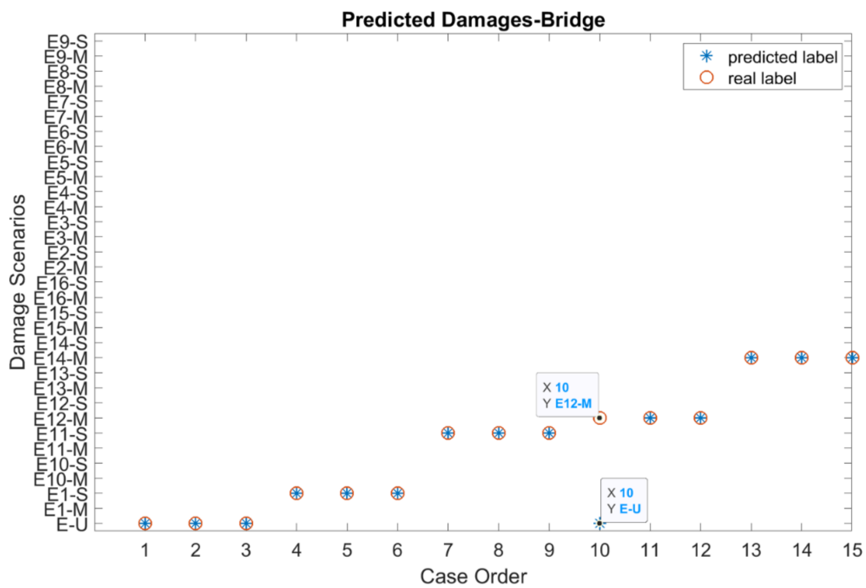
The experimental validation results are shown in Figure 14, to eliminate the measurement error, three measurements of each damage scenario are processed in the trained ML network for damage prediction. In which, one of the E12-M (member 12 moderate damage) case is wrongly predicted as E-U (undamaged) case, however, the rest of two measurements show the correct results. Therefore, in the real-time bridge damage prediction environment, this bridge has a high probability of moderate damage at member 12.

Figure 14. Predicted Damages-Bridge Model



Summary and Conclusion

This project explored a new approach to conduct ML-based structural damage detection with the integration of model updating technique. The hybrid approach realizes a real-time application of structural health monitoring which timely fill the inspection gap by identifying critical damages before out of control.

To verify the proposed idea, a miniature bridge model was prepared, and its structural responses were synchronized with a numerical FEM model through the model updating technique. As a result, the FEM model emulated the real model’s structural behaviors. Through the updated model, various damage scenarios were simulated, and corresponding data were generated for ML training.

In addition, a new perspective to perform structural dynamic feature extraction is introduced. The idea of borrowing the pre-trained models, enhances the performance of the prediction and improves the time efficiency. By utilizing wavelet transform, the vibration measurements can be easily converted from time-domain data into time-frequency multi-domain information. It constructively avoids the high computational demands from modal extraction. The application of an image-based deep learning network improves the efficiency of damage detection. A FEM of a frame bridge is built to validate the proposed method as a case study. Resnet is adopted to perform transfer learning and resulted in a testing accuracy of 97%

Through the project, our findings are as follows: 1) The proposed method integrated with a sensor-based system enables to continuously monitor structural integrity. As a result, when critical structural elements are damaged, the proposed method clearly and informed damage locations (global inspection) and their severity (local inspection). 2) Current biannual inspection may miss the critical and dangerous damage growths before the next inspection cycles. The proposed continuous monitoring timely filled the inspection gap by identifying critical damages before out of control. 3) No additional cost for system improvement is required if a sensing system is already installed on a bridge structure.

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Data Management Plan

Data Format and Content

1) FE model and updating module (numerical model format: Tcl and m): for model updating MALAB code were written, and OpenSees FEM model was built with a tcl file.
2) Structural response data from numerical bridge model (training and validation file format: jpg): All structural responses data were collected through sensors. All data were converted with wavelet jpg image format.
   Deep learning network algorithms (algorithm format: m): deep learning algorithms
3) Documentation (recording format: docx, pdf): thorough this project, 1) one conference paper and 2) one final report were submitted.

Data Access and Sharing

All participants in the project will publish the results of their work. A conference paper including reports are primary source of data sharing. The data will be available to the public except sensitive or confidential data. The PIs shared data through Google Drive. Anyone from the public domain will be able to register as a user of such a system to get access to selected project documentation for research and educational uses.

Reuse and Redistribution

All participants in the project published the results of their work. The conference paper and the final report are primary source of data sharing. In addition, the data for structural responses and FEM models including ML code are available to the public except sensitive or confidential data. For sharing purpose, the PIs set up Google Drive as the link below.

https://drive.google.com/drive/folders/1udLejmXy5ZVjpbO64zTC5xAYitAxjvdO?usp=sharing

Plans for Archiving and Access to Data

Research data were achieved in digital format on the PI's lab computers and/or in file servers and made freely available. Therefore, research products were made available after publication. Conference or journal (in the future) publications will be available online.