Quarterly Progress Report

Project Number and Title: 3.8 Bridge Modal Identification via Video Processing and Quantification of Uncertainties
Research Area: Thrust 3 – New Systems for Longevity and Constructability
PI: *Zhu Mao, University of Massachusetts Lowell*
Co-PI(s): *Co-PIs and home institution(s)*
Reporting Period: *07/01/2021-09/30/2021*
Date: *09/30/2021*

Overview: **(Please answer each question individually)**

This project has as objective investigate the capability of applying non-contact optical sensing and motion magnification to identify structural dynamics and damage in a truss bridge. Previously, experiments on the equipment were performed in the Olney Hall Bridge, on the campus of UMass Lowell, and then an in-situ test of the new Grist Mill Bridge, located at Hampden, Maine was conducted as part of Project C11. During this reporting period, the test was performed and the data collected were processed in order to obtain dynamic information of the bridge. We also communicated with our Technical Champion at MassDOT and identified several different bridges to test on, and test was performed on the Lowell Connector Bridge across Howard Street at Lowell. The objective of this test was to compare the results obtained using PME with different optical techniques, including a commercial system from RDI for vide-based data extraction. In addition to the test, the study using machine learning for damage detection was continued.

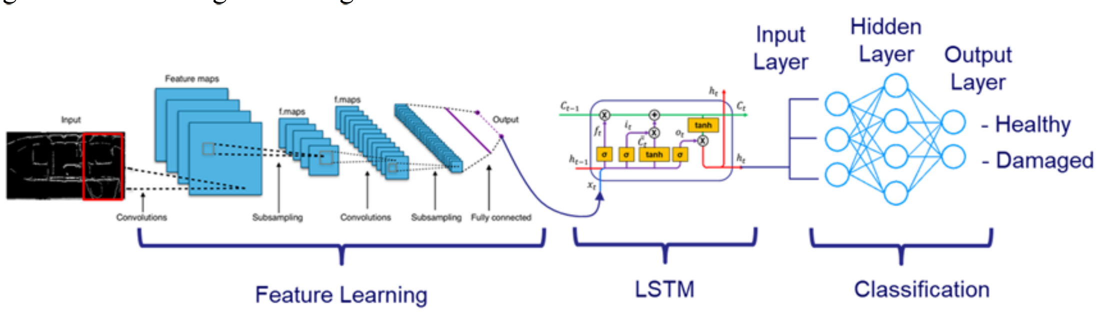
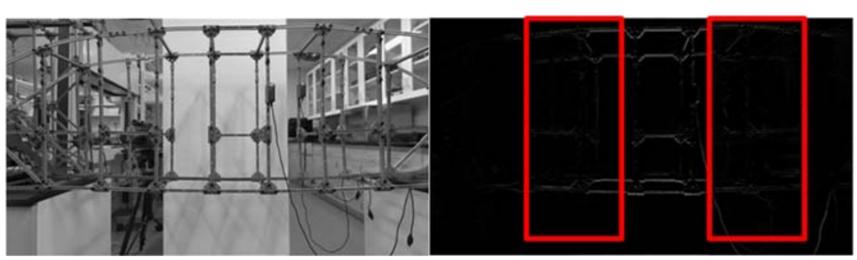


Figure 1. Flowchart of CNN-LSTM algorithm.

Previously, an algorithm using Convolutional Neural Networks (CNN) was developed using as input the magnified video of a lab scale bridge vibrating at its first natural frequency to classify if the bridge was damaged or not. However, since CNN algorithms does not consider the temporal dependence between the frames of the video, the final accuracy was lower than expected. Now, in addition to the CNN, it was added a Long Short-Term Memory (LSTM) network to include the temporal dependence in the features extracted by the CNN algorithm to increase precision. Figure 1 shows the flowchart of the CNN-LSTM model. The process to obtain the input for the algorithm is similar to what was done for the CNN algorithm. From the video recorded of the bridge, initially the Phase-based Motion Magnification (PMM) algorithm was applied at its resonant frequency to amplify the subtle motion of the structure, thus, making visible the bending mode shape of the structure. Since the video has many features in the background, its first frame was used as reference and the subsequence frames were subtracted from the first, allowing to extract only the movement of the bridge. Also, since the damage done in the bridge is removing one of its linkages. In order to hide the damage and use only the dynamic information for the damage detection – such as, change of natural frequency and mode shape – a section of the frames was selected where the damage is not visible. In Figure 2 it is possible to verify a) the original frame of the video and b) the frame after processing.



(a) (b)
Figure 2. (a) Frame of the bridge, (b) frame of the bridge after background removal.

The framework of the algorithm also starts similarly to the previous CNN technique. Using the frames from the video, different kernels will be applied into each frame to extract features of the system. The kernels are applied in three different layers, with a pooling function to down sample the original image. The difference in the technique occurs in the output of the convolutional part of the CNN algorithm i.e., after flattening the features obtained by the convolutions. The output will then be used as input for the LSTM layer in groups of frames. The LSTM structure can be seen in figure 3. The input in the image, identified as x_t will be convoluted with the results from the previous layers (h_{t-1}), this convolution will be applied into an activation function. Depending on the weight obtained by the activation function it will be determined if the information from the previous layer, known as cell state (C_{t-1}) will be forgotten or not, also, the cell state will be updated with the information of the input of this layer. The multiplication of the activated cell state with the convolution of the input from the current layer and output of previous layer will be the output of the current layer (h_t). After all layers were applied, the final output will be used for the neural network to recognize the patterns of a health and damaged structure, allowing the model to predict damage of new videos.

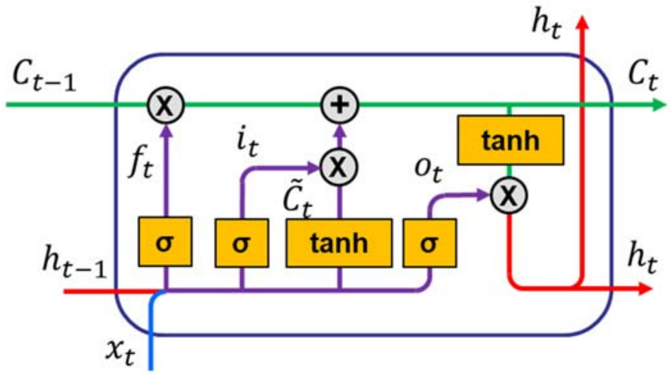


Figure 3. Structure of LSTM layer.

For the parameter tuning, some of the parameters were kept as the same as the previous CNN algorithm. Those values can be seen in Table 1. However, since some of the parameters can have a high impact on the final result, it was done trainings combining different values, so that it would be possible to obtain the optimal result. In figure 4 it is available the parallel plot showing the accuracy when varying batch size, the number of time steps and the number of LSTM layers.

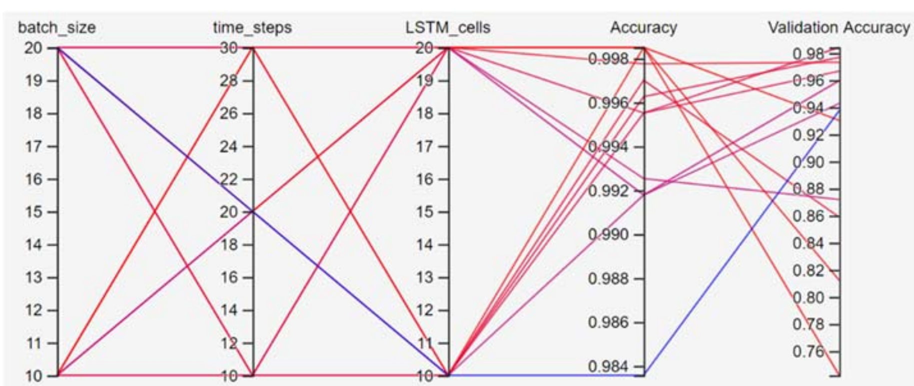
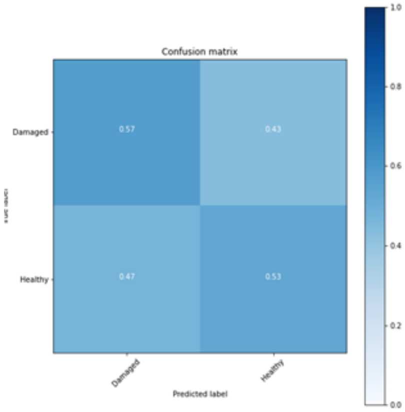
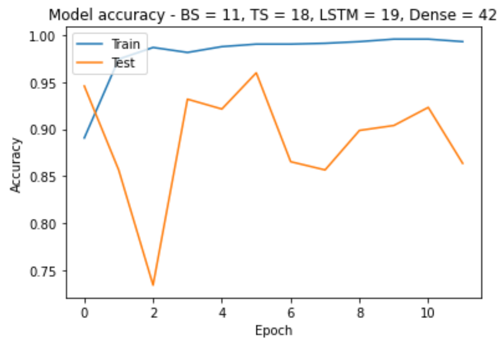


Figure 4. Parallel plot of the training and validation accuracy versus the parameters of the algorithm

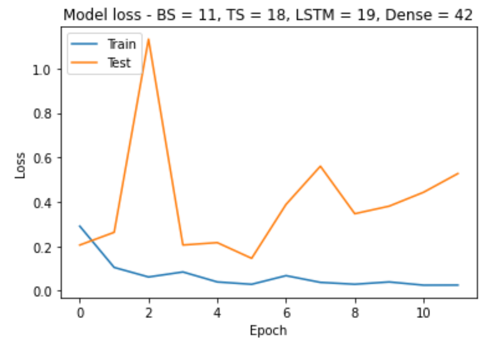
The preliminary results using one of the best combination of parameters can be seen in Figure 5. Although the accuracy and loss shown in Figure 5 b) and c) are better than the obtained by the CNN technique alone it is still possible to improve the final result. In Figure 5a) it is possible to verify that even though the validation and training accuracy is good, the confusion matrix with the predictions still does not have effective results. Therefore, other possible combination of parameters will be studied, aiming for reduction of possible overfitting and increase in accuracy for prediction. Other techniques to prevent overfitting and improvements in the structure of the algorithm will be analyzed as well.



(a)



(b)



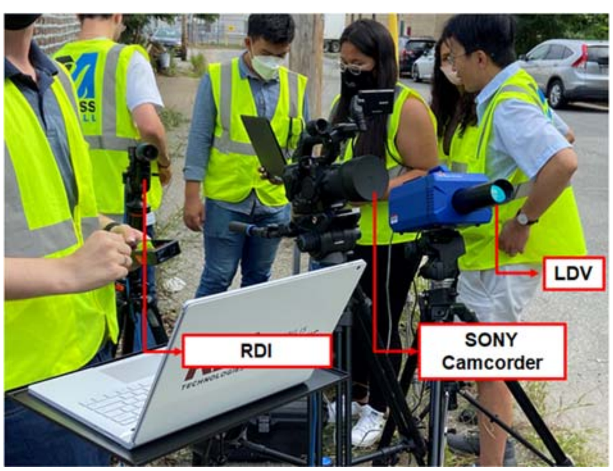
(c)

Figure 5. Preliminary (a) Confusion matrix, (b) model accuracy and (c) loss for the CNN-LSTM algorithm.

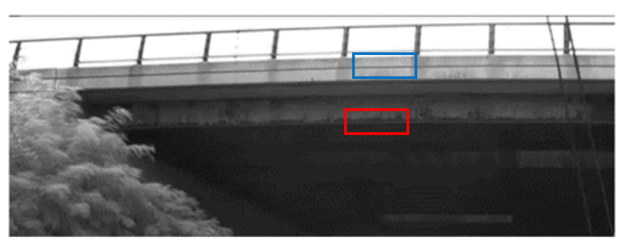
Table 1: Parameters of the Convolutional Neural Network

	LAYER 1	LAYER 2	LAYER 3
CONVOLUTIONAL LAYER	k(3*3)/c(32)	k(3*3)/c(32)	k(3*3)/c(64)
MAX POOLING LAYER	k(4*4)	k(4*4)	k(4*4)
ACTIVATION FUNCTION	ReLU	ReLU	Sigmoid
EPOCHS	12		
BATCH SIZE	11		
TIME SAMPLES	18		
NUMBER OF LSTM LAYERS	19		

In addition to the study using machine learning to predict damage, a test was performed at the Lowell Connector bridge, at Howard Street. This test was done to extract dynamic information of the bridge during normal operation – using as load cars and trucks passing – using different optical techniques. For PME and PMM it was acquired full HD recordings at 60FPS at 22m distant from the bridge, leading to a 17.9mm/pixel resolution, which allows to extract motion in the order of 2mm of amplitude. To compare the results obtained by PME and PMM it was used a commercial high-speed camera from RDI. This equipment is capable to extract full field motion at 109FPS, although it has a higher frame rate than the traditional camcorder, it has the drawback of having more equipment to assemble, making it less portable than the PME. Figure 6a) shows the equipment used for the test, while Figure 6b) and c) shows the field of view from RDI and the camcorder respectively.



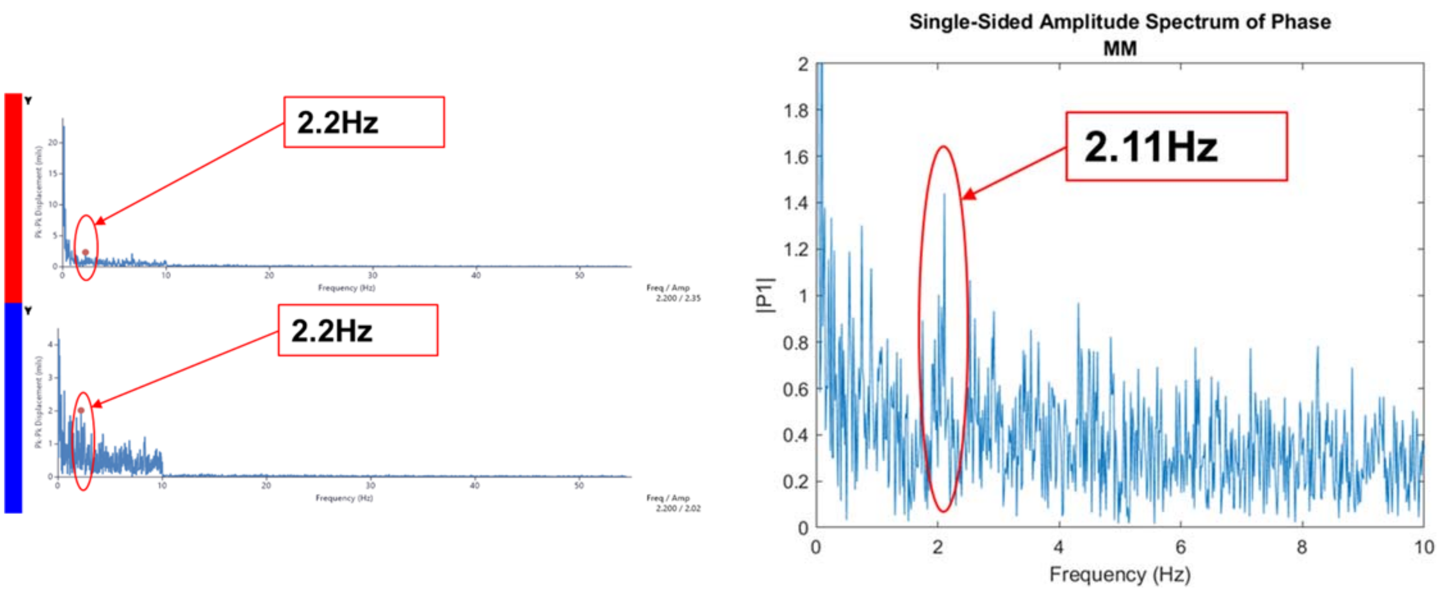
(a)



(b) (Top) and (c) (Bottom)

Figure 6. (a) Setup for the Lowell Connector bridge test. Field of view of (b) RDI equipment and (c) SONY camcorder (used for PME).

Preliminary results show a good agreement between the data collected by each of the video-based equipment. The initial focus of the data analysis is mainly in the frequency response extraction in order to identify the mode shapes of the bridge. The results from RDI and PME can be seen in Figure 7a) and b) respectively. For the RDI software, it was used two different regions of interest, to analyze the effect of the contrast and illumination in the video. The regions of interest can be seen in Figure 6b) as a red and blue rectangle. As for the PME, the region of interest was in a similar location to the RDI software. The frequency response also showed a similar resonance frequency for both methods. Next steps are the comparison of the video-based results with the LDV data, which has higher precision and is well stablished for vibration analysis. Also, the comparison of the time response for the amplitude of motion between the RDI software and the method described in the last report, which aims for quantification of PME.



(a) (b)

Figure 7. Frequency response obtained by (a) RDI and (b) PME.

The data collected in this test showed great potential for structural health monitoring of bridges, since the video-based techniques poses a portable solution for data acquisition. In addition, the data recorded posses full-field information of the structure and the techniques enable mode shape and natural frequencies extraction at any given point or region. In addition, with continuous monitoring, it is possible to generate a dataset to be used later in data-driven techniques, such as, the CNN-LSTM algorithm described in the report for damage detection. Although the CNN-LSTM algorithm is in its initial results, it already had a better training and validation accuracy than the CNN technique alone and has potential to accurately detect damage.

Table 1: Task Progress

Task Number	Start Date	End Date	% Complete
Task 1: video motion magnification	9/1/2019	5/30/2021	85%
Task 2: non-contact modal analysis	9/1/2019	9/1/2020	100%
Task 3: machine learning	9/1/2019	8/31/2021	70%
Task 4: nonlinear modal analysis	1/1/2020	12/31/2021	20%
Overall Project:	9/1/2019	12/31/2021	

Table 2: Budget Progress

Project Budget	Spend – Project to Date	% Project to Date*
$55219.5 (project extended to the next phase with funding renewed)	$ 59786.05	100% as of 9/30/2021

Include the date the budget is current to.

Table 3: Presentations at Conferences, Workshops, Seminars, and Other Events				
Title	**Event**	**Type**	**Location**	**Date(s)**
Bridge Modal Identification via Video Processing and Quantification of Uncertainties	TIDC 1st Annual Conference	Conference meeting	UMaine	June 6-7, 2019
Bridge Modal Identification via Video Processing Motion Magnification	Northeastern Society for Experimental Mechanics Conference	Conference	UMass Dartmouth	June 22nd, 2020
Bridge Modal Identification via Video Processing and Quantification of Uncertainties	TIDC 2nd Annual Conference	Conference meeting	UML	August 12, 2020
Optical-Based Structural Health Monitoring of Truss Bridges	2020 TIDC Annual Student Poster Contest	Competition	Online	October 21,2020
Infrastructure State Awareness and Dynamics Identification via Advanced Sensing	NEC Laboratories America, Inc.	Seminar	Online	January 4, 2021
An Optical Mode Shape-Based Damage Detection Using Convolutional Neural Networks	International Modal Analysis Conference	Conference	Online	February 11, 2021
A Comparative Analysis of Imaging Processing Techniques for Non-Invasive Structural Health Monitoring	International Workshop on Structural Health Monitoring	Conference	Stanford University	TBD upon the pandemic
Finite Element Modeling of Pavement and State Awareness using Fiber Optic Sensing	International Workshop on Structural Health Monitoring	Conference	Stanford University	TBD upon the pandemic
Vibration-Based Status Identification of Power Transmission Poles	International Workshop on Structural Health Monitoring	Conference	Stanford University	TBD upon the pandemic

An Optical Temporal and Spatial Vibration-Based Damage Detection using Convolutional Neural Networks and Long Short Term Memory	International Modal Analysis Conference	Conference	Orlando, FL and online option available	February 2022
Digital Twin for Dynamic Characteristics and Prognostics via Deep Learning and Advanced Sensing	Worcester Polytechnic Institute,	Seminar	Worcester, MA	September 2021

Table 4: Publications and Submitted Papers and Reports				
Type	**Title**	**Citation**	**Date**	**Status**
Conference Proceedings	Motion magnification for optical-based structural health monitoring	https://www.spie.org/SS20/conferencedetails/health-monitoring-structural-biological-systems	04/27/2020-04/30/2020	Full paper published
Conference Paper	An Optical Mode Shape-Based Damage Detection using Convolutional Neural Networks		0/11/2021	Full paper in press

Participants and Collaborators:

Table 5: Active Principal Investigators, faculty, administrators, and Management Team Members			
Individual Name	**Email Address**	**Department**	**Role in Research**
Zhu Mao	Zhu_Mao@uml.edu	Mechanical Engineering	PI
Tzuyang Yu	Tzuyang_Yu@uml.edu	Civil Engineering	Collaborating on bridge testing and sensor placement; providing lab-scale testbed for algorithm validation
Xingwei Wang	Xingwei_Wang@uml.edu	Electrical Engineering	Collaborating on bridge testing and sensor placement; providing lab-scale testbed for algorithm validation

Table 6: Student Participants during the reporting period				
Student Name	**Email Address**	**Class**	**Major**	**Role in research**
	Email is not included in the external report and is only used for internal purposes.	(i.e. Junior, Master's Ph.D)		
Celso do Cabo		Ph.D.	Mechanical Engineering	Key personnel to conduct the theoretical investigation

Nicholas Valente		Ph.D.	Mechanical Engineering	Idea discussion, and helping on tests and data processing
Emi Aoki		M.S.	Electrical Engineering	Data processing

Table 7: Student Graduates			
Student Name	**Role in Research**	**Degree**	**Graduation Date**
Aral Sarrafi	Key personnel to conduct the theoretical investigation	Ph.D.	Spring 2019
Matthew Southwick	Idea discussion, and helping on tests	M.S.	December 2020

Table 8: Research Project Collaborators during the reporting period						
Organization	**Location**	**Contribution to the Project**				
		Financial Support	**In-Kind Support**	**Facilities**	**Collaborative Research**	**Personnel Exchanges**
NEC Laboratories America, Inc.	Princeton, NJ	x		x	x	

Table 9: Other Collaborators			
Collaborator Name and Title	**Contact Information**	**Organization and Department**	**Contribution to Research**
Gregory Krikoris	gregory.krikoris@state.ma.us	MassDOT	Technical Champion

Changes:

The PI has just transferred to Worcester Polytechnic Institute, and would like to keep working on the remainder of Project 3.8 upon the approval from TIDC. The PI still maintains an Affiliate position at UMass Lowell to keep working on the unfinished projects.

Planned Activities:

In the next reporting period, we will focus on the following challenges.

- Identify and isolate the mode shapes of the Grist Mill bridge based on the data collected
- Study the possible methods of nonlinear modal analysis and choose the best approach to the truss-bridge structure
- Compare non-contact sensing with traditional sensing modalities in a metallic structure
- The lab-scale truss bridge will be kept utilized for testing new models of data extraction to provide realistic data.
- Non-contact sensing will be adopted and more in-depth investigation of selecting pixels, especially a big number of pixels to take advantage of the averages. By doing this, a better estimation of the modal information will be expected, but this is contingent on the data quality at the selected pixels. Trimming and cropping the videos prior to calculating the expected resonance frequencies may also help enhance the performance.
- Applying other sensing modalities, and maybe collaborating with other projects, in identifying frequencies using conventional data acquisition method. This will help design a better band-pass filter in getting mode shapes and motion magnification results. This effort will be cohered with other UMass Lowell faculty.
- Machine learning algorithms will be studied in the next reporting period to provide an improvement of the results of this period and an option in classifying different damaged types and possibilities for damage localization.

- Collaborate with NEC Labs America.
- Comparison of Grist Mill Bridge and Howard Street Bridge results obtained from multiple sensing modalities
- Improvement of current model, by changing the type of materials, elements and excitation to obtain a more realistic model