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: *01/01/2020-03/31/2020*
Date: *03/31/2020*

Overview:

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. In the last reporting period, the research activities may be sketched as:

- Identify a lab-scale linear-behaved metallic truss model for a benchmark bridge testing set up
- Investigating the feasibility of using machine learning to identify vibrational modes and damages

The literature review embraced from load estimation using camera-based data and identification of damage with the static deformation generated by the estimated load done by Zaurin and Catbas [1] and the use of this methodology when the deformation is measured with non-contact sensing from Dong et al. [2]. It also researched studies which focus into limitations of the noncontact sensing, as comparing the data achieved from camera with a finite element model and accelerometers from Chen et al. [3]. and techniques of using camera-based sensing without markers as Dong et al. [4]. Damage identification using machine learning was also investigated, for example in studies done by Gordan et al. [5], which shows data mining-based methods for damage identification.

Looking for nonlinear analysis, besides Worden [6], who decomposed the nonlinear mode shape with principal orthogonal decomposition using machine learning, other studies, such as Chanpheng [7] who used the existence of nonlinearity in a structure after a drastic change in the structure, as an earthquake as damage identification and Worden et al. [8] who identified nonlinear behavior in linear structures after damage. However, even with the exploration done for this approach. It is still needed further investigation of techniques that can be used for the current project.

After investigating the second approach, which was using camera-based sensing for full-field mode shape analysis. Some studies were found as Hoskere et al. [9], who used drones to assemble partial mode shapes of large structures into one full-field mode shape, or Javh et al. [10] who used the aid of accelerometers to extract full-field mode shapes at high frequencies using cameras with low frequency acquisition.

In addition, Gorjup et al. [11] who used one camera from different observation points to extract a 3D mode shape of a complex structure. Yang et al. [12] who developed a method to blind identify a mode shape and motion magnification, Also Yang et al. [13] used full field mode shape to do damage localization using fractal dimension in beams.

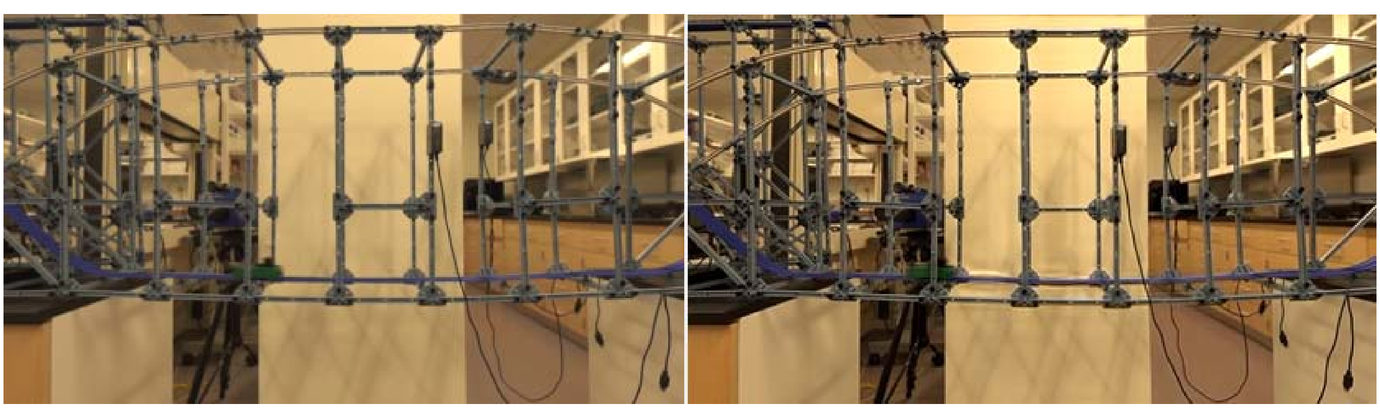
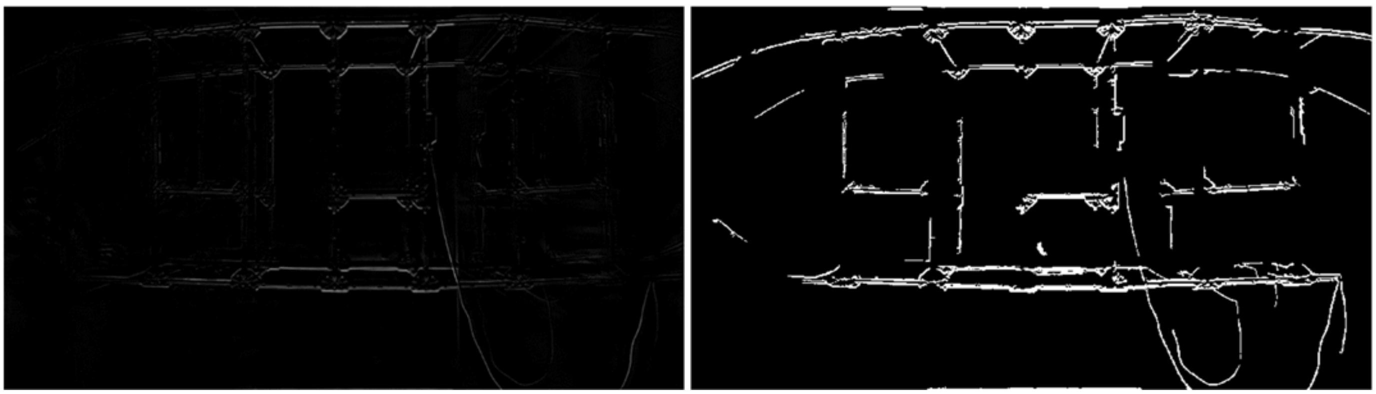

(a) (b)

Figure 1. Bridge model testing (a), bridge model testing with motion magnification (b).

Starting from the studies in full-field analysis techniques and machine learning for damage identification. The focus was on how to identify damage from the mode shape of the structure. In order to achieve that, it was used a machine learning algorithm with convolutional neural network to observe the pattern of the mode shape of a healthy and a damaged structure. Initially it was used a severe damage for testing the method. The main idea was applying motion magnification into the structure so the mode shape could be amplified. As the deformation changes with the load of the structure many frames of the video were used as input. In Figure 1 it is possible to see the difference in one frame between a case with (b) and without (a) motion magnification.



(a) (b)

Figure 2. Subtraction of frames (a), subtraction of frames with contrast increased (b).

However, as the frames are similar and the background of the video has many details, it was applied part of the computer vision algorithm, created in a previous period of this project, to subtract the frames from a static reference, in order to display just the movement of the bridge. With that, only the moving parts would be shown to the algorithm reducing details from the background and to highlight the movement. In addition, it was increased the contrast of the image to improve the visibility of the dynamic parts. Thus, the frames showing the movement were the input of the algorithm. In Figure 2 it is possible to verify the subtraction of the frames with a static reference(a) and the same subtraction with a higher contrast.

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(a)

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(b)

Figure 3. Output of the algorithm for a given number of frames of a damaged structure (a), and a healthy structure(b).

Showing a similar set of images to the trained model it would classify it as damaged, using 0 or healthy, using 1. Applying this model into many frames recorded and averaging them is the best option to tell if the structure is healthy or not. Since the frames with small movement would be just a black picture. Figure 3 shows an example of the output of the software. Each number is a frame analyzed by the model. Figure 3(a) are damaged frames and (b) healthy frames. These preliminary results showed difference between the damaged to the healthy case, however it is still not a reliable method to identify the damage as the result for a healthy case identifies just around 48% of the frames as healthy. While the damaged are identified as healthy in 35% of the frames.

For the next reporting period it is planned to keep the study on how to improve this algorithm for damage identification and as a goal create a model for damage localization. In parallel it is planned to start tests comparing the camera-based and traditional sensing to metallic truss structures, which has higher natural frequencies if compared to the truss model. Figure 4 shows how the truss structure is and its boundary conditions for the testing. It is also planned tests in a real truss bridge inside the campus of the University of Massachusetts, Lowell.

Figure 4. Metallic truss structure for future testing.

The activities in this period led to a better understanding of the techniques that can be applied for damage identification in truss structures. It also showed potential for the algorithm of damage identification using just the mode shape and camera-based sensing.

Table 1: Task Progress			
Task Number	**Start Date**	**End Date**	**% Complete**
Task 1: video motion magnification	1/1/2019	5/31/2019	100%
Task 2: non-contact modal analysis	1/1/2019	9/1/2019	100%
Task 3: machine learning	9/1/2019	12/31/2020	20%
Task 4: nonlinear modal analysis	1/1/2020	12/31/2020	10%
Overall Project:	1/1/2019	12/31/2020	

Table 2: Budget Progress		
Project Budget	**Spend – Project to Date**	**% Project to Date***
$55219.5	$25432.12	46% as of 03/31/2020

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	April 18th, 2020

Bridge Modal Identification via Video Processing and Quantification of Uncertainties	TIDC 2nd Annual Conference	Conference meeting	UML	September 2020

Table 4: Publications and Submitted Papers and Reports				
Type	**Title**	**Citation**	**Date**	**Status**
Conference Proceedings	Motion Magnification and Machine Learning for Optical Based Structural Health Monitoring of a Truss Bridge	TBD	04/27/2020-04/30/2020	Accepted

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

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
Matthew Southwick		Ph.D.	Mechanical Engineering	Idea discussion, and helping on tests

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

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**
N/A						

Table 9: Other Collaborators			
Collaborator Name and Title	**Contact Information**	**Organization and Department**	**Contribution to Research**
N/A			

Who is the Technical Champion for this project?
Name: John (Jack) Moran
Title: Deputy Chief of Performance and Asset Management and Director of Asset Management
Organization: MassDOT
Location (City & State): Boston, MA

Changes:

In addition to the planned modal identification approaches that will be applied, machine learning and nonlinear modal analysis will be adopted too. Review of literatures has been deployed in the past reporting period, and these new techniques will be a successful complement to the bridge assessment.

Planned Activities:

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

- 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 and in an on-campus truss bridge
- 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.

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