CAMERA-BASED BRIDGE SAFETY MONITORING

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ABSTRACT

This paper describes a research project focused on the safety assessment of bridges using camera-based technologies. It is a collaboration with partners in three countries: Ireland, the United Kingdom and the United States.

A major challenge of the project is the development of algorithms and methods that transform the measured sensor signals and video images into a form that is highly damage-sensitive/ change-sensitive for bridge safety assessment. The study will exploit the unique attributes of computer vision systems, where the signal is "continuous in space." This research will significantly advance current sensor-based structural health monitoring with computer-vision techniques, leading to practical applications for damage detection of complex structures with a novel approach.

In the long term, monitoring with cameras is expected to be more broadly utilized for structural engineering purposes because of its potential for inexpensive deployment in real life bridges. While advancing the knowledge by integrating multidisciplinary concepts from theory to application, this research will have direct benefits as civil infrastructure (and particularly aged bridges) has become a critical societal concern from safety and cost perspectives.

The paper will describe the bridge monitoring system that will be developed. It will include a weigh-in-motion (WIM) system to weigh vehicles, with cameras to monitor both the traffic and the bridge. The WIM system and the 1st camera will track the traffic and will extract its properties. The 2nd camera with some supplementary sensors will monitor the response of the bridge to the traffic. Structural identification algorithms will transform all of this data into damage indicators that indicate when the bridge has deteriorated or changed. The system will be tested using numerical simulation, scale models in the laboratory and trials using full scale bridges in the field.

Keywords: Bridge, SHM, camera, image, damage.

1. INTRODUCTION

This paper describes a new project, started in the Autumn of 2015 and funded under the US/Ireland Research and Development partnership. This programme funds partners in 3 jurisdictions: the United States of America (US), the Republic of Ireland and Northern Ireland in the United Kingdom. Each partner is funded by agencies in their own countries but the review process is that of the US National Science Foundation.

As illustrated in Figure 1, the concept is the simultaneous monitoring of the inputs and the outputs of a vehicle bridge system. The inputs are the vehicles crossing the bridge and these will be monitored by cameras and image analysis software that identify the locations and configurations of each vehicle. In addition, a weigh-in-motion (WIM) system will be used to weigh each axle of the passing vehicles. The outputs of the system are the bridge responses. These will be monitored by additional cameras, other sensors and software that processes the data into damage indicators which indicate the probability that the bridge condition is poor. The numerical models will be validated using laboratory trials and field monitoring of full scale bridges before and after scheduled repairs.

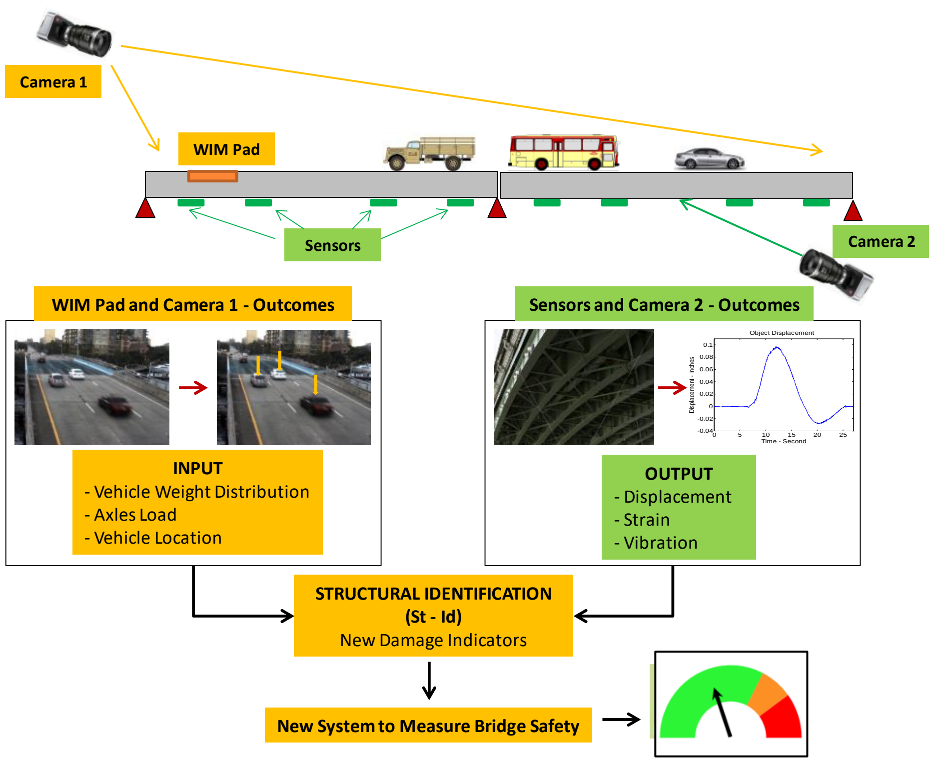

Figure 1: Schematic of project proposal.

2. IMAGE ANALYSIS

As illustrated in Figure 1, traffic loads induced from multiple vehicles are estimated, including their amplitudes and locations, by utilizing a series of advanced computer vision algorithms on image data from a traffic camera. Simultaneously, another camera (response camera) is deployed under the bridge deck to measure bridge displacements in response to those vehicles by means of a non-target vision-based displacement monitoring method (Khuc & Catbas, 2014). The input data (traffic loading) and the output data (displacement responses) are provided to a novel St-Id system to form new indicators for bridge damage detection, named displacement Unit Influence Surfaces (UIS). UIS is an improved 2D version of the Unit Influence Line (UIL), which was shown to be obtained experimentally before and utilized in the laboratory as well as in real life bridge structures (Catbas et al, 2012; Zaurin and Catbas, 2011, 2010; OBrien et al, 2006).

2.1. Multiple-vehicles Detection and Localization using Computer Vision Approach

Using advanced computer vision algorithms, vehicles in traffic can be tracked and then categorized into classes by processing image data (video clips) from a surveillance camera on the bridge. Since the weight distribution of each vehicle class can be studied from manufacture's vehicle specifications and/or using a Weigh-In-Motion (WIM) database, a detected and classified vehicle is assigned to a distribution weight corresponding to its class. In this study, the Haar (Viola & Jones, 2001) and/or HOG (Dalal & Triggs, 2005) features corresponding to a particular class of vehicles are extracted to represent that type of vehicle. Those object features are used to develop a classification algorithm based on a booting technique (Viola & Jones, 2001), which can rapidly find regions where a particular class may occur in an image from the surveillance camera. The initial and successful implementation for tracking and classifying small-scale vehicles has been deployed in the laboratory (Khuc and Catbas, 2015a).

Localizing those detected vehicles crossing a bridge in the 3-D world coordinate (x, y, z) is another part of developing Unit Influence Surfaces. From the previous section, the detected vehicles are located in the 2-D image coordinate (u_{pixel}, v_{pixel}) by extracting information from bounding boxes. Since the bridge deck surface can be assumed as a plane, the 3-D world coordinate of vehicle locations will be simplified to the 2-D coordinate corresponding to length and width of the bridge deck. Thus, the relationship between the 2-D image and the 2-D world coordinate is solved by using a Planar Geometric Transformation approach as follows:

$$\mathbf{W}_{\mathbf{coordinate}} = \mathbf{T} \times \mathbf{I}_{\mathbf{coordinate}} \tag{1}$$

or, $$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & 1 \end{bmatrix} . \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \tag{2}$$

where **T** is a transformation matrix to map $\mathbf{W_{coordinate}}$ to $\mathbf{I_{coordinate}}$. Since the **T** matrix has eight (8) unknown elements, those elements are determined by solving a collection of at least 8 relationship equations between the world points and the corresponding image points. Assigning fifteen (15) reference points on the bridge deck, the **T** matrix is established by using the least squares fit algorithm for an over-determined system as there are 15 relationship equations to estimate 8 unknown variables.

2.2. Obtaining the Displacement Unit Influence Surface

Displacement Unit Influence Surface (UIS) at a particular position i^{th} (called a measured point) on a bridge structure is defined as a displacement function to the unit load at every position of the unit load on bridge deck. Since the value of unit load equals one, a UIS can be mathematically presented as a two-variables surface as shown in equation (3):

$$R = \mathrm{UIS}_i(x,y) \tag{3}$$

where (x,y) are the coordinates of the unit load location on the bridge deck. R is a displacement value at the i^{th} measured point due to the unit load at (x,y). The locations (x,y) of the unit load are obtained from multiple vehicle positions that are determined as described in section 2.1. Meanwhile, the structural displacement values of R are acquired by the non-target vision-based displacement monitoring (Khuc & Catbas, 2014, Khuc and Catbas, 2015b). As the data of locations (x,y) and displacements (R) are discrete, the UIS is estimated by fitting those discrete data sets.

A displacement UIS of a laboratory bridge at the UCF laboratory is shown in Figure 2. It is seen that each blue dot location (x-bridge length, y-bridge width) represents a combined position from multiple vehicles on the bridge deck. The z-unit displacement value of a particular blue dot is a normalized displacement induced by these vehicles. Quantitative analysis of the UIS has confirmed its consistency and reliability that enables its use in damage detection and damage localization.

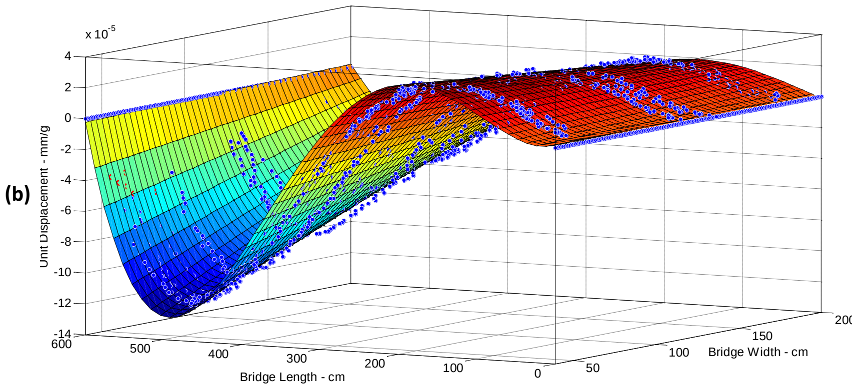

Figure 2: The displacement unit influence surface of a laboratory bridge

3. OTHER DAMAGE DETECTION ALGORITHMS

In an alternative approach, data will be collected over enough time to collect a ‘population’ of bridge responses to trucks of a given class. It has been shown (O’Connor et al, 2000; Wilson et al, 2006 – see Figure 3) that the mean pattern of dynamic forces applied by a population of trucks to a *pavement* is repeatable. The dynamic response of a bridge to a truck is a complex vehicle/bridge dynamic interaction problem. In this project, we will consider the dynamic responses from a population of similar trucks. It is a reasonable hypothesis that the mean of the population of dynamic responses will be highly repeatable and independent of the particular properties of any one truck. Further, as these measurements will be taken over a long period of time, the mean of the population of responses will be independent of short-term environmental factors such as the daily temperature cycle. Any change in the mean dynamic response of the bridge to the truck population is a strong indicator that the bridge has been damaged. The research question will be to explore whether the dynamic response of a bridge to a population of trucks is repeatable and how sensitive is that dynamic response pattern to bridge damage.

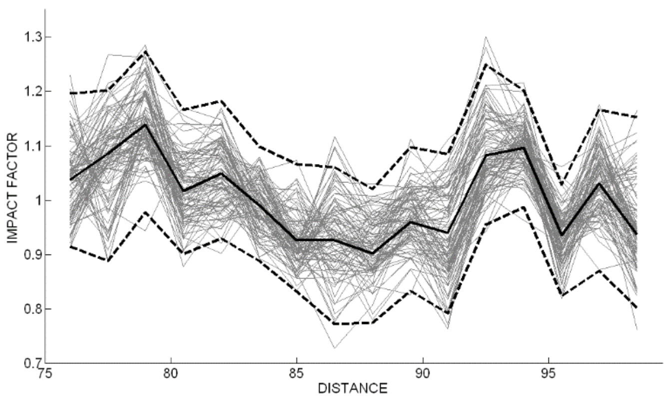

Figure 3: Dynamic forces applied by axles to a road, with mean and confidence interval

To remove the variability due to axle spacings and to increase the pool of data from which useful information can be extracted, an Inverse Bridge Weigh-in-Motion (WIM) algorithm will be applied. Bridge WIM is the problem of finding truck weights from the bridge response. Inverse Bridge WIM is the problem of finding the bridge behaviour, given the response and the trucks axle weights. The bridge behavior is described by the inferred influence line, i.e., the response to a unit point load (Figure 4). Any change in the inferred influence line is a good indication that the bridge has deteriorated, e.g., a bearing has seized. The challenge with this problem is when truck axle weights are not known. However, Inverse Bridge WIM theory can still be applied using typical values for the relative axle weights for each vehicle type. As a result, there will be considerable variation in the calculated influence lines. The hypothesis is that this variation will not be excessive and that the mean shape of influence line will provide useful data that can be combined, perhaps in a Bayesian framework, with other information collected by the bridge inspector.

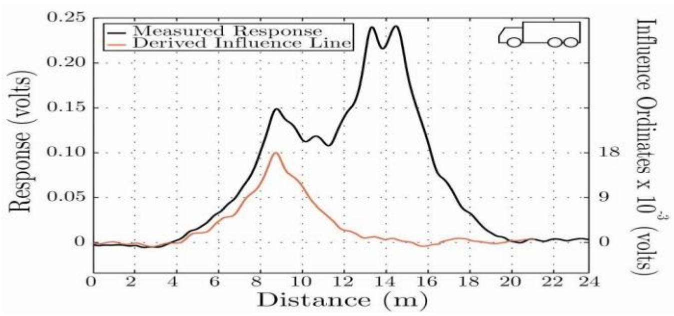

Figure 4: Sensor response to 3-axle vehicle and inferred influence line

4. FIELD TRIALS

To test the camera-based monitoring approach, one bridge has already been instrumented and two more are planned. The first bridge site selected for these trials is situated in Loughbrickland, Northern Ireland, along the A1 dual carriageway which forms the main corridor connecting the cities of Belfast and Dublin. This route through the island has a high traffic volume which made it an optimum location for Bridge Weigh-in-Motion (BWIM) as there are 10,000 to 12,000 vehicles travelling on the carriageway in each direction daily. Additionally, the bridge is in close proximity of a static weigh station for local enforcement of axle and gross weights and has also been installed with a range of below deck sensors for BWIM as described in previous research (Lydon et al, 2014 & 2015). The bridge, which was constructed in 2010, is an integral concrete structure with a 19 m span (Figure 5). The deck consists of 27 prestressed precast concrete Y4 beams, each 1 m in depth, spaced at 1.22 m centres. There is a 200 mm deep cast in-situ concrete deck supported by non-structural permanent formwork spanning transversely between the main beams. The bridge has an angle of skew of 22.7°. Lane 1 of the northbound carriageway has been instrumented for BWIM research as part of another research project. Fibre Optic sensors were installed on the girders at various locations to provide data for a conventional BWIM installation. Sensors were also installed at the supports for axle detection. Additional sensors are located on the deck slab to improve the accuracy of axle detection and investigate sensitivity to variations in vehicle transverse lane location. These additional sensors ensure that local wheel strains are not missed. All fibre optic sensors were connected back to the light source and interrogator mounted with the processing computer. The research has benefited from collaboration with the Driver and Vehicle Agency (DVA) of Northern Ireland who randomly select vehicles to be weighed at the nearby Weigh Station. The DVA weight result information was compared with the predictions from the BWIM installation.

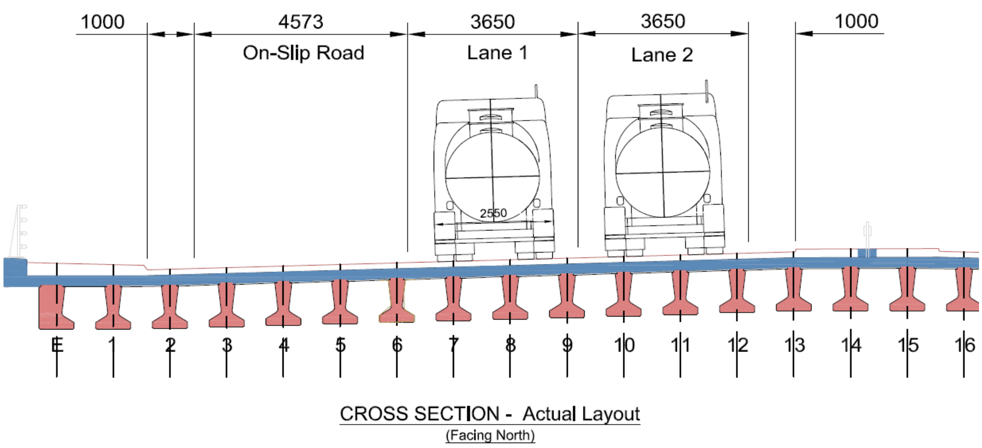

Figure 5: Cross-section Test Bridge Deck

5. FIELD RESULTS

Measurements were taken on site over one day and the BWIM predicted vehicle weights were compared to the measured weights from the static weighing. Eight vehicles were statically weighed, namely; three 5-axle vehicles, two 2-axle vehicles and one vehicle each with three, four and six axles. Due to the limited sample size, the influence line calibration was carried out using just the three five axle vehicles. These were chosen as they are the most frequent truck type in the sample. The influence line was calculated using the matrix method developed by OBrien et al. (2006). The axle spacings were determined using the video images of the vehicles crossing the bridge. The synchronisation of two cameras meant that the axle spacings could be calculated from the number of frames between the axles passing a notional vertical line in the frames. A complication in both the calibration process and WIM calculation arises due to the unknown point at which the vehicle and bridge interact. This is partly because of the integral nature of construction which causes the axles to apply force through the soil to the bridge before arriving on the deck. In addition, because of the skew, the wheel on the right-hand side of the vehicle enters the bridge first and this is the opposite side from the camera. This problem is addressed through an optimisation process. Table 1 summarises the results and shows that results are generally accurate for gross weight.

Table 1: GVW error using CBWIM

	Vehicle No.	No. of Axles	Gross Weight Error
I.L. Calibrat-ion	1	5	-11.5%
	2	5	-4.1%
	3	5	5.7%
Testing	4	2	-9.3%
	5	2	0.9%
	6	3	-13.7%
	7	4	-6.9%
	8	6	-2.3%

6. CONCLUSIONS

This paper describes a new collaborative project on camera-based monitoring of bridges. It will use a combination of approaches to monitor the traffic load on bridges and their responses to that load. The new approaches will be tested through numerical simulation, in the laboratory and in full scale field trials.

7. ACKNOWLEDGMENTS

The National Science Foundation, Science Foundation Ireland, the Department for Employment and Learning Northern Ireland, and Invest Northern Ireland are gratefully acknowledged for their financial support.

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