Title: **Camera-based Triggering of Bridge Structural Health Monitoring Systems using a Cyber-Physical System Framework**

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ABSTRACT

A cyber-physical framework is proposed in this paper to integrate the measured response of two highway bridges and a weigh-in-motion system located along the same highway corridor. Leveraging traffic images captured by existing traffic cameras, computer vision techniques such as histogram of oriented gradients are utilized to detect trucks in images and synchronize measured vehicle-induced bridge data and truck weights with images of vehicle loads. Those images then act as a cyber-based linkage connecting the bridge monitoring systems and a weigh-in-motion system. Such a data fusion strategy makes it possible to establish a clear input-output model for each bridge system and explore the correlation between the responses of different bridges to same trucks. In addition, the camera system can also be used to trigger bridge monitoring systems intelligently to measure more truck events with a limited monitoring system power supply.

INTRODUCTION

Innovative bridge health monitoring systems have been developed over the last decade to facilitate data-driven approaches to bridge health management. Structural health monitoring (SHM) systems typically focus on a single bridge including measurement of its environment and corresponding response to loads [1,2]. However, the emergence of the Internet has driven new and exciting modes of connectivity between physical systems. In the United States highways are being transformed by this connectivity including the emergence of connected vehicles and intelligent transportation systems (ITS). The SHM of bridges can greatly benefit from these advances including integration of SHM data with other ITS data such as camera feeds and direct quantification of vertical loading imposed by heavy trucks [3]. This study explores the integration of three sources of data relevant to bridge SHM: wireless sensor data collected from instrumented bridges, traffic cameras monitoring traffic flow, and data from weigh-in-motion (WIM) systems. The 20-mile-long I-275 corridor between Monroe and Romulus, Michigan is established in

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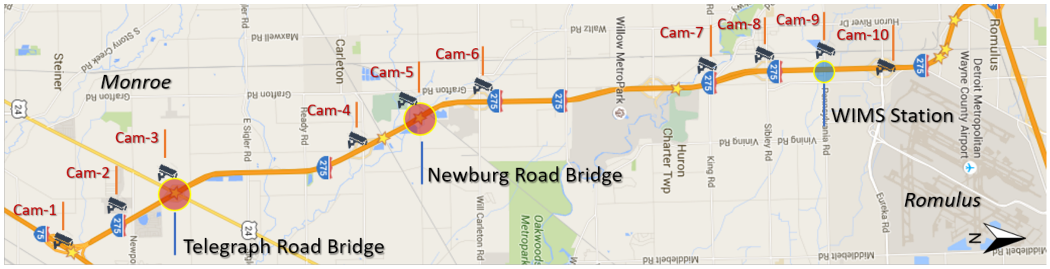

Figure 1. Spatial distribution of CPS system elements on the I-275 NB highway corridor.

this study as a test environment to explore the use of traffic camera feeds to track trucks loads traveling northbound from Monroe to Romulus. Along the 20-mile stretch are two highway bridges (Telegraph Road Bridge and Newburg Road Bridge) instrumented with wireless sensor networks for long-term bridge health monitoring, one WIM station, and 10 traffic cameras (Figure 1). The study integrates these data sources into a cloud-based environment [4] where traffic camera feeds are automatically processed to identify trucks in the network. As trucks travel northbound, two bridge wireless monitoring systems are triggered in a serial fashion to capture bridge responses to specific truck events. In the meantime, the cloud keeps fetching traffic images which bridge response data can be synchronized with afterwards from the traffic flow monitoring system. Similarly, the framework seeks to identify the truck at the WIM station to derive a quantitative measurement of the truck weight. In doing so, the wireless monitoring systems of the bridges are capable of triggering the measurement of bridge response to the same truck event to allow for response comparisons to be made. Furthermore, load information is derived from the WIM station for the truck event allowing for a more rational approach to assessing bridge capacities because on load-response measurements.

CPS ARCHITECTURE

This project integrates the heterogeneous set of data collected from three types of data collection systems: bridge SHM systems, weigh-in-motion (WIM) systems and traffic camera systems. The bridge SHM system utilizes wireless sensing technology measuring bridge responses to vehicle loads [1]. Collected bridge data can serve as the basis of assessing bridge structural conditions and estimating vehicle properties (e.g., weight, speed) through dynamic interaction between the bridge and vehicles. WIM stations can measure weights and weight distribution of vehicles without slowing down the traffic. The traffic monitoring system is an array of traffic cameras deployed along the highway to monitor traffic flow in real time. Bridged by traffic images, the cyber-physical framework proposed in this study intelligently links the measured bridge responses (i.e., system outputs) to WIM records (i.e., system inputs). As a result, correlation of responses of different bridges to the same vehicle loads can be established and a clear input-output model can be built for each instrumented bridge system. The highway corridor on I-275 northbound (NB) between Monroe and Romulus, Michigan is selected as the testbed for the proposed framework. The entire system including two bridge monitoring systems, one WIM station and 10 cameras is illustrated as Figure 1.

Figure 2. Telegraph Road Bridge (left) and Newburg Road Bridge (right).

Bridge Health Monitoring System

Along the corridor, two instrumented highway bridges, the Telegraph Road Bridge (TRB) and the Newburg Road Bridge (NRB), are both built in 1973 and owned by the Michigan Department of Transportation (MDOT). Shown in Figure 2 left is the TRB which is a multi-girder composite steel bridge located in Monroe. It spans 224 feet (68.28 m) in total including a main span of 128 feet (39.01 m) and two wing spans each 48 feet (14.63 m). The main span is connected to the cantilever ends of the two wing spans through pin-hanger assemblies while the wing spans are supported by concrete piers. Carrying three lanes of I-275 NB, the TRB consists of seven girder lines underneath a steel reinforced concrete deck. The NRB, also presented in Figure 2, is a single span bridge with a length of 105 feet (32.00 m) located 4.5 miles downstream (north) of the TRB. It also carries three lanes using seven steel plate girders and a composite reinforced deck.

The two bridges are both instrumented with the long-term automated wireless sensor network (WSN) to measure bridge responses to passing vehicles. A WSN is composed of a number of *Narada* [5] sensing nodes and a base station. In a sensing node, the sensors, strain gages or accelerometers, are interfaced with the *Narada* wireless sensing unit through conditioning circuits (e.g., low-pass filters) and a 16-bit ADC. Each node is powered by a 12V 3.2Ah sealed lead acid (SLA) battery which is charged by a 12W solar panel. The base station of each bridge is used to send operational commands to the wireless sensing nodes (e.g., sleep), collect sensor measurements from nodes and forward data to a cloud database [4]. Their primary components are one single board computer (Winsystems PPM-LX800-G) which is connected to Internet over LTE and one CC2420 RF transceiver connected to an external high-gain omni-directional antenna. The base stations are powered by 12V 40Ah SLA batteries with 160W solar panels.

This study applies Hitec HBWF-35-125-6-10GP-TR weldable strain gages, BDI ST350 strain transducers, and Silicon Design 2012-002 uniaxial accelerometers for the measurements of steel girder strain responses, concrete slab strain responses and acceleration responses, respectively. Weldable strain gages are welded to the web-bottom of girders to measure the longitudinal bending strain caused by vehicle loads. BDI gages are bolted to the bottom surface of the bridge slab to measure the local tensile strain caused by direct wheel loads, which is commonly used as an axle detector in bridge weigh-in-motion (BWIM) technology [6]. Accelerometers are mounted to the bottom flange of girders to measure vehicle-induced vibrations in the bridge. Based on the measured acceleration, the TRB and NRB exhibit a first modal frequency of 2.4Hz and 4.2 Hz, respectively. Accordingly, the sampling rate is set to be 100 Hz for strain gages and 200 Hz for accelerometers. In addition, a few thermistors (LM35DT) are also installed

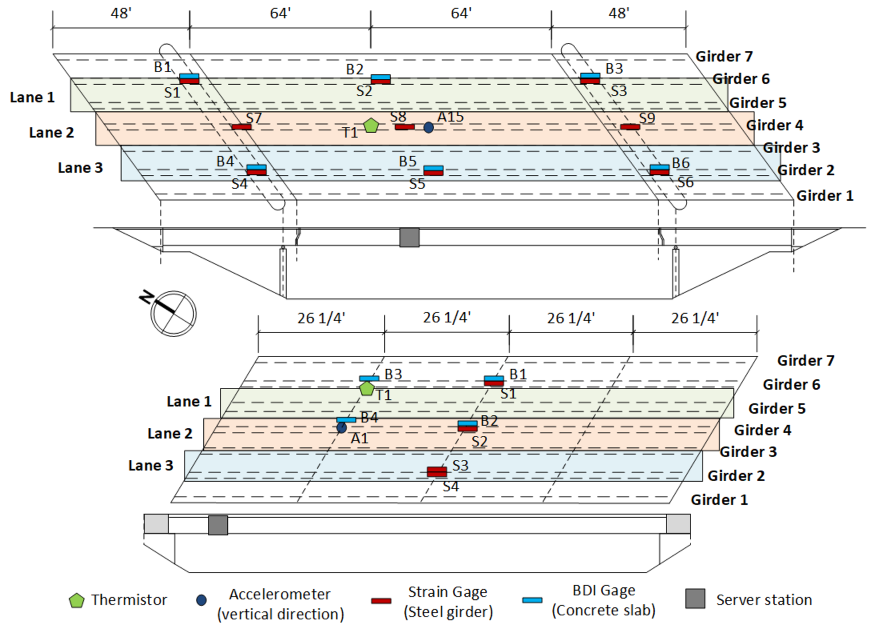

Figure 3. Sensor layout on TRB (top) and NRB (bottom) with sensor types defined.

to measure the ambient temperature of the bridge. The TRB system was installed in 2011 while the NRB system was newly installed in 2016. Their current sensor layout is shown in Figure 3.

Weigh-in-Motion System

Highway weigh-in-motion (WIM) stations play a vital role in highway traffic monitoring systems. WIM stations, with sensors installed within the road pavement, are capable of continuously estimating the gross weight (i.e., static weight) of a vehicle as well as the load distribution of weight carried by each axle or axle group on the vehicle. In addition to weight, vehicle signatures such as the number of axles, axle spacing and speed are also recorded. Compared to traditional scale stations, the WIM station is more cost efficient because it obtains measurements without slowing down the highway traffic. Relying on truck weight information collected, governments can conduct truck weight limit enforcement more efficiently. The WIM station underneath the Pennsylvania Road Bridge at the north end of I-275 in Romulus is used in this study for providing information of truck weight. It is the only WIM station on this segment of I-275. One caveat though is the presence of 4 exits which allow trucks to enter and exit the highway. This fact further justifies the need for camera and computer vision to track trucks.

Traffic Monitoring System

The traffic monitoring system is a traffic video network managed by MDOT. All images captured by the traffic cameras are available to the team in real time. There are 10 cameras located in the range of the corridor as labelled in Figure 1. The network updates images at each location every 2 seconds but sometimes the update interval can increase to 10 seconds due to network latency. Each image has a resolution of 352x240

Figure 4. Traffic images captured by road cameras: cam-3 at TRB (left); cam-5 at NRB (middle); cam-9 at WIM station (right).

pixels. Three example images are shown in Figure 4 where the same truck traveling north on I-275 is presented.

DATA INTEGRATION

The data integration process can be delineated into two stages: 1) online stage and 2) offline stage. The online stage includes tasks that are processed at the time of data acquisition while the offline stage is primarily in charge of matching the measured bridge responses with the WIM records using traffic images. Traffic images at Newport Road, Telegraph Road, Newburg Road and Pennsylvania Road which correspond to camera-2, camera-3, camera-5 and camera-9 (in Figure 1), respectively, are used for truck tracking. A truck detector is trained for each location by means of computer vision and machine learning techniques including histogram of oriented gradients (HOG) and support vector machine (SVM).

Truck Detector

HOG is a feature descriptor widely used for object detection [7]. A feature descriptor can be interpreted as a representation of an image containing useful information of the image. In the HOG descriptor, histograms of directions of gradients are used as features. Each sample image is divided into a number of cells each 8x8 pixels in size. Distributing the directions of unsigned gradients into 9 bins by a voting mechanism based on magnitude of gradients, each cell can be represented by a 9-entry vector. After a block normalization process for illumination invariance, each image can be represented by a feature vector concatenated from all block feature vectors.

At each location, 2000 image patches of trucks are cropped from traffic images as positive samples and 4000 patches of non-truck objects (e.g., pavement, small vehicles) are cropped as negative samples. Some examples of cropped images from camera-3 are shown in Figure 5. Considering the size of traffic images is only 352x240 pixels which leads to an even fewer number of pixels associated with the trucks in the images, all the samples are resized to 32x40 pixels and the input image size of the HOG trainer is modified accordingly instead of the default 64x128 pixels. Except the input image size, all the other parameters are set as per the original paper [7]. As a result, each sample patch has a feature vector of 432 entries.

After the HOG feature extraction, the obtained feature vectors are fed into a linear

Figure 5. Positive samples (top) and negative samples (bottom) from traffic cameras.

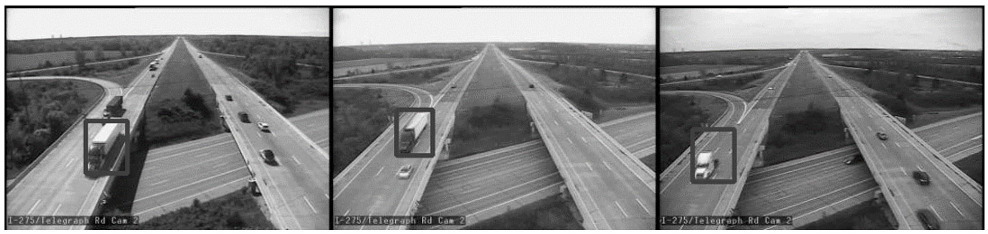

Figure 6. Detection results on images of cam-3 at TRB.

support vector machine [8] for training in order to learn an SVM truck detector. This procedure is realized through a package called SVM-light [9]. The detection task is then implemented using the OpenCV library [10] in Python. During the detection, several sliding windows with different scales are scanning through an image to determine if a truck appears in any position. As can be seen in Figure 5, within images of a certain camera, most trucks have a very similar graphic pattern in that they all have a contour with a near diamond shape in the cropped patches, which makes it easier for the linear SVM classifier to accurately detect trucks. The resulting classifier owns a precision of 95% and a recall of 78%. Some qualitative detection results on images of cam-3 are presented in Figure 6.

Online Data Integration Stage

Online data integration involves triggering the bridge monitoring systems and synchronizing measured bridge responses with traffic images. A computation node deployed on Windows Azure cloud service is used to facilitate the fusion process. Shown in Figure 7, the cloud keeps fetching images from cam-2 and conducting truck detection in real-time. Once a truck is detected at the location of cam-2, the cloud will send wake-up messages to the TRB and the NRB monitoring systems in a consecutive fashion to activate the data acquisition (DAQ) processes on a schedule based on their distances (which dictates travel times) to cam-2. In the meantime, the cloud starts to crawl photos from cam-3, cam-5 and cam-9 accordingly and stores them into a NoSQL database [4]. After the DAQ process on the TRB and the NRB, the base stations at each bridge will upload collected data to the cloud. A strain peak detection script will then run on the collected bridge response data to detect dominant strain peaks that are larger than a threshold (e.g., 15 micro-strain). Those strain peaks are assumed to correspond to heavy loads (i.e., trucks) running over the two bridges. Based on the time stamps of those strain peaks, traffic images are queried from the database and matched with the bridge responses.

Offline Data Integration Stage

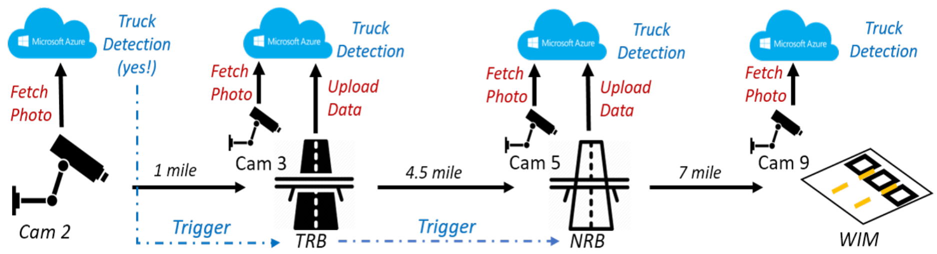

Figure 7. Online stage of data fusion process.

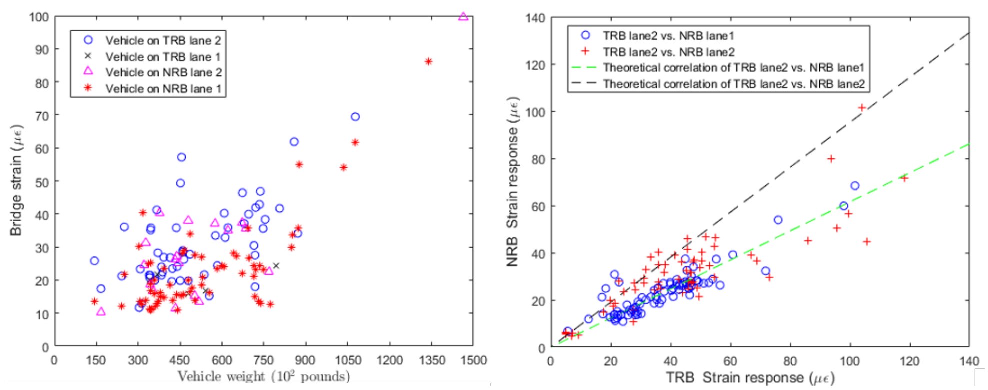

Figure 8. Correlation between vehicle weights and bridge strain responses (left); comparison of bridge strain responses of two bridges (right).

Offline data integration refers to the process of matching trucks detected at the two bridges and the WIM station based on traffic images. To the best of the authors' knowledge, because of the low resolution, no existing computer vision algorithm can extract a sufficient number of repeatable and distinct features from a truck image patch to robustly recognize matches in other images. Consequently, this matching process is conducted manually without the use of computer vision techniques. This task is even challenging to human operators. An example of matched traffic images is shown in Figure 4 where the logo printed on the side of the truck is the key visual feature used for matching.

The correlation between the maximum truck-induced bridge strain response and the gross weight of corresponding truck is plotted in Figure 8 for the TRB (sensor S8) and the NRB (sensor S2); as expected, there exists a positive correlation between them. In addition, presented in Figure 8 is a comparison between strain responses measured at both bridges using data from the same pair of sensors. Measured data points are scattered around the theoretical relationship obtained from finite element model simulation using the truck weight. In the plot, lane 1 refers to the slow lane while lane 3 refers to the fast (passing) lane, as shown in Figure 3.

CONCLUSION

This study proposed and implemented a cyber-physical system (CPS) framework to link multiple bridge monitoring systems with a nearby weigh-in-motion station taking advantage of computer vision techniques to identify truck events. This approach to data fusion makes it possible to match measured bridge responses to corresponding input loads. The platform can serve as a testbed for bridge load rating, BWIM algorithm validation and other applications that are difficult to conduct without load information. Since the low resolution of traffic images constrains the level of automation that can be attained in the current framework and the accuracy of truck detection/matching, some ongoing work is focused on improving the performance of the system by replacing current traffic cameras with high-resolution cameras, training deep learning models for faster and more accurate truck detection and developing automated truck matching program.

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