Computer Vision Oriented Framework for Structural Health Monitoring of Bridges

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Nomenclature Table

Ir,Ig,Ib	Input image color intensities (red, green and blue).
Mr,Mg,Mb	Background mean intensities (red, green, and blue).
σ_r, σ_g, σ_b	Background standard deviation intensities(red, green, and blue)
λ	Assumed threshold for foreground detection.
U_{image}, V_{image}, S	Image coordinates.
f	Focal length
k_x, k_y	Effective size of the pixel in mm.
X_{world}, Y_{world}, Z_{world}	World coordinates
r	Coefficients of the camera rotation matrix (3x3).
tx,ty,tz	Spatial translation of the camera.
ox,oy	Image center
v	Velocity of an object circulating over the bridge.
d	Distance between centroids of the same object in consecutive frames
t	Time between two consecutive frames (1/30 s.)
Change	Normalized variation from the input image with respect to the model.

ABSTRACT

Novel structural health monitoring strategies for better managing of civil infrastructure systems (CIS) are increasingly becoming more important as CIS are aging and subject to natural and man made hazards. Bridges constitute a critical link of the transportation network hence; any damage or collapse could result in loss of humans' life and also has a negative effect in regional and national economy. The objective of this research is to propose and implement a novel framework for structural health monitoring of bridges by combining computer vision and a distributed sensors network that allows not only to record events but to infer about the damaged condition of the structure. Video stream will be used in conjunction with computer vision techniques to determine the class and the location of the vehicles moving over a bridge. The video input will also be used for surveillance purposes. A database will be constructed using information from vehicles training sets, experimental results from the sensors network and, analytical models. Then, the proposed system, by interpreting the images and by correlating those with the information contained in the database, will evaluate the operational condition of the bridge and/or will emit alerts regarding suspicious activities.

1. INTRODUCTION AND SYSTEM OVERVIEW

Structures are complex engineered systems that ensure society's economic and industrial prosperity. To design structures that are safe for public use, standardized building codes and design methodologies have been created. Unfortunately, structures are often subjected to unexpected loading scenarios and severe environmental conditions not anticipated during design that will result in long-term structural damage and deterioration. To design safer and more durable structures, the engineering community is pursuing novel sensing technologies and analytical methods that can be used to rapidly identify the onset of structural damage in an instrumented structural system [1], [2]. Structural health monitoring (SHM) paradigm offers an automated method for tracking the health of a structure by combining damage detection algorithms with structural monitoring systems. Structural Health Monitoring can be defined then as measurement of structural responses under an operational environment to track and evaluate incidents, anomalies, damage, deterioration etc [3].

Very recently, some investigators have contemplated the possibility of incorporating imaging and optical devices and combining them with sensing technology however, only a few limited attempts have been tested and implemented. A framework for intelligent sensor network with video camera has been suggested by researchers, prescribing the use a mote sensors network to monitor a structure [4]. The use of video cameras was intended to monitor traffic and other activities on the bridge. Video cameras were intended to be triggered when the activity metric is higher than some threshold, indicating that there is significant vibration in that particular section. Another framework was proposed, combining a network sensors array, a database for storage and archival, computer vision applications for detection and classification of traffic, probabilistic modeling structural reliability and risk analysis and damage detection with preliminary concepts and limited implementations [5]. In a similar study one of the main objectives was the use of video analysis of pre-recorded data, computer vision algorithms, and artificial intelligence as a mean to classify and keep records of traffic (type, number of vehicles, velocity, peak strain readings) circulating over a fiber reinforced composite deck used as test bed [6]. One of the main contributions of the system proposed in this research is the direct relation between cause and effect, i.e., loads (traffic) with sensors readings are studied by means of sensor networks and video stream. Most of the previous work was based on studies just on ambient vibration and couldn't differentiate ambient or traffic readings, unless testing was scheduled by closing the bridge. The framework proposed in this study consists of five main components, integrated and closely interrelated as is described below: the vision module, the distributed sensors network array, the analytical model, the database, and the diagnostic module (Figure 1). By knowing the position and magnitude of moving loads; sensors readings and video is synchronized and the structure is monitored at every instant by using operational traffic.

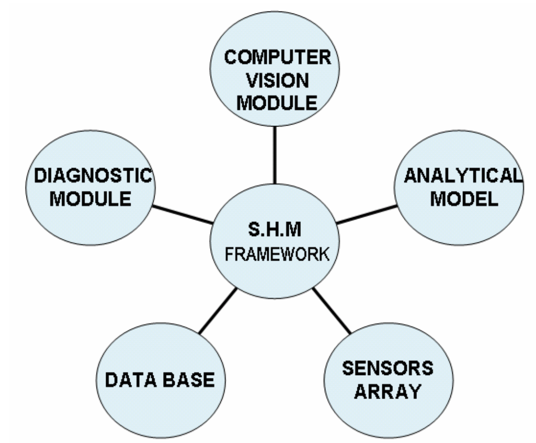


Figure 1.
Integrated framework for the proposed system

1.1. The Vision Module:

In the beginning, vision capabilities will be used to build the database. Input from video cameras will be correlated with the sensor network array readings.

1.1.1. Training phase:

Video cameras located at the top of the bridge, will detect and classify the traffic, or any other object, moving over the structure. In this phase, the type of vehicle (load), velocity, and position, will be correlated with the sensors readings and with the finite element model in order to create the database. Data like deflection, strain, and rotation, from sensors responses, will be stored for type of vehicle, number of axles, speed, minimum and maximum relation of weight, and axle spacing. Those effects will be normalized by decomposing and converting them in unit influence lines coefficients (Figures 2,3).

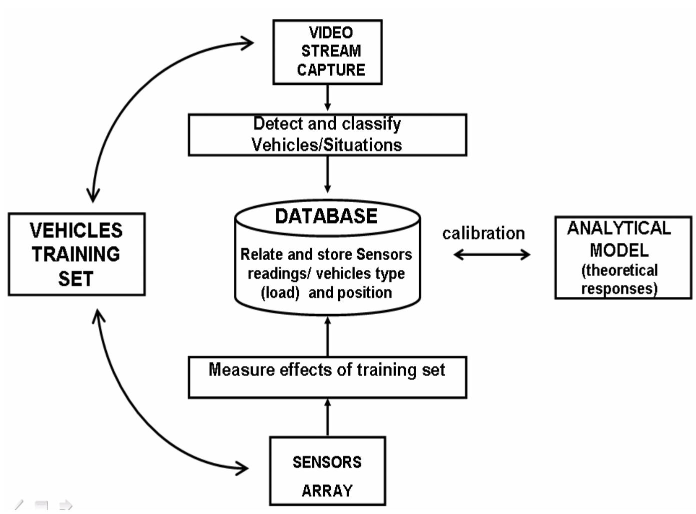


Figure 2. Training Phase

1.1.2. Operating phase

The set of cameras located on top of the bridge will be used again but this time they are in charge of detecting, tracking and classifying moving loads and/or suspicious activities (Figure 3).

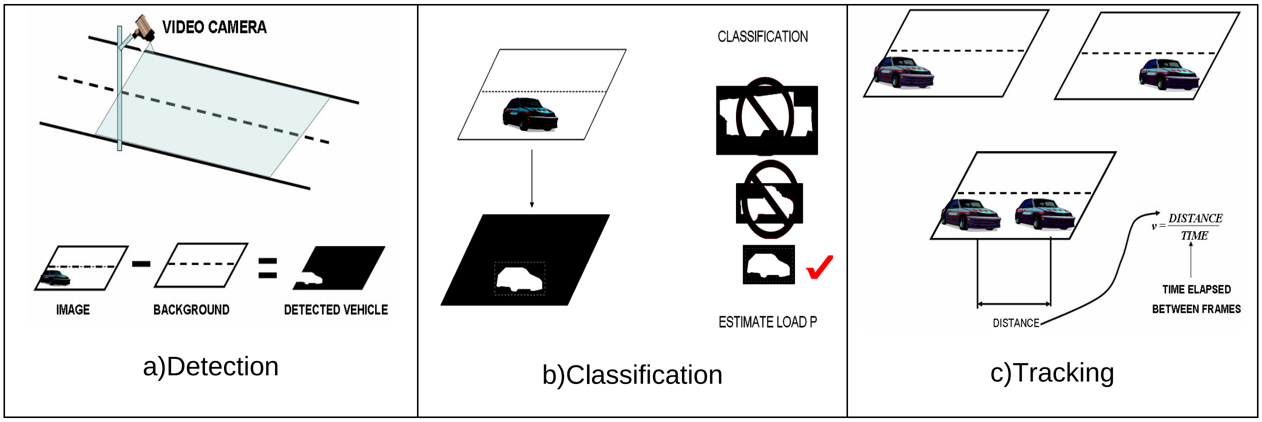


Figure 3. Vehicle detection, classification, and tracking.

1.2. Distributed sensors network array

The bridge will be instrumented with all necessary kind of sensors including, but not limited to, strain gages, accelerometers, tilt meters and, deflection meters (Figure 4). Deflection, strain, rotation, time history response data and modes of vibration of the structure will be correlated with the video input and the analytical model will be calibrated as well.

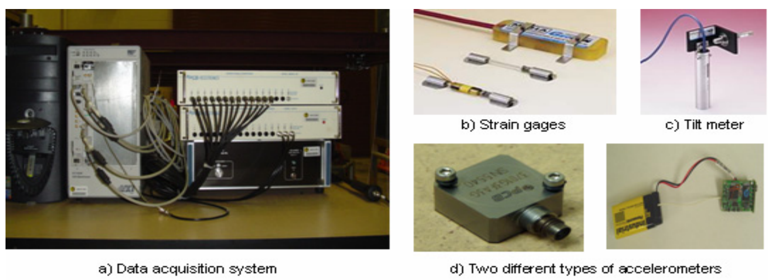
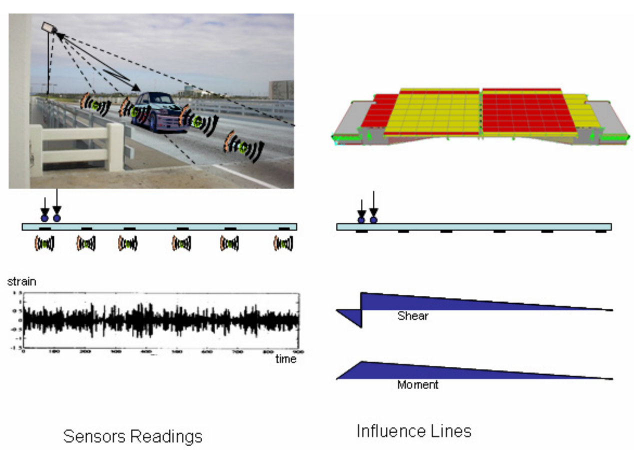


Figure 4. Sensors instrumentation equipment



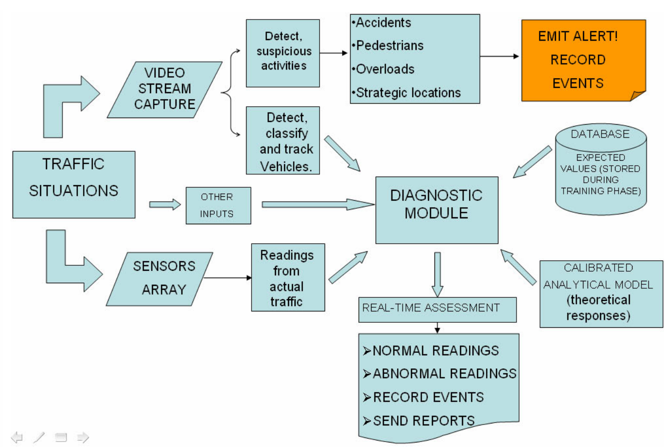


Figure 5. Sensors/video/analytical model correlation.

Figure 6. Overall system scheme

1.3. Analytical Model

The structure will be analyzed by means of a Finite Element (FE) or another analytical model. This model will allow predicting the theoretical behavior of the bridge under any given load combination. Of course, the model will be calibrated with the experimental results from the cameras and the sensors array (Figure 5).

1.4. Database

The core of the system containing the expected structural behavior under traffic loads will be stored in the database. This database will be constructed using training vehicle sets detected by the vision module and correlating this information with the sensors array and, the analytical model. The number of training sets will be determined after a statistical study of the type of common traffic over the bridge is completed. Critical information to be stored will include type of vehicle, number of axis, loads for each axis, position, velocity, and corresponding readings from all the sensors at different locations. The database can and will be updated as necessary.

1.5. Diagnostic Module

Once an input is received from the vision module, the system will infer about the structure health by comparing the expected results for those loads (from the database) with the actual readings (from the sensors array) as is shown in figure 6. Surveillance capabilities will also discern between normal and suspicious activities and emit alerts if needed.

2. FIELD IMPLEMENTATION

Implementation of the framework started on a movable bridge property of the Florida Department of Transportation (FDOT). This special type of structures requires of a high maintenance budget (about 100 times that of fixed bridges) and is object of frequent breakdowns, and malfunctions that cause not only problems in land but also for marine traffic. A representative movable bridge was selected as test bed for the proposed SHM framework (Figure 7).

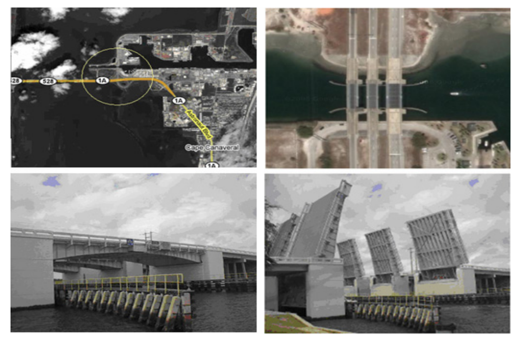


Figure 7. Case Study: Bridge S.R. 401

2.1. Analytical Model

Once the case study was selected, the following step was to create an analytical model representing the bridge. Using SAP 2000, a FE model was created to evaluate the most critical structural behavior for monitoring purposes. The bridge model was analyzed under a normalized vehicular load corresponding to the HS20-44 truck for detecting critical structural locations to monitor (Figure 8).

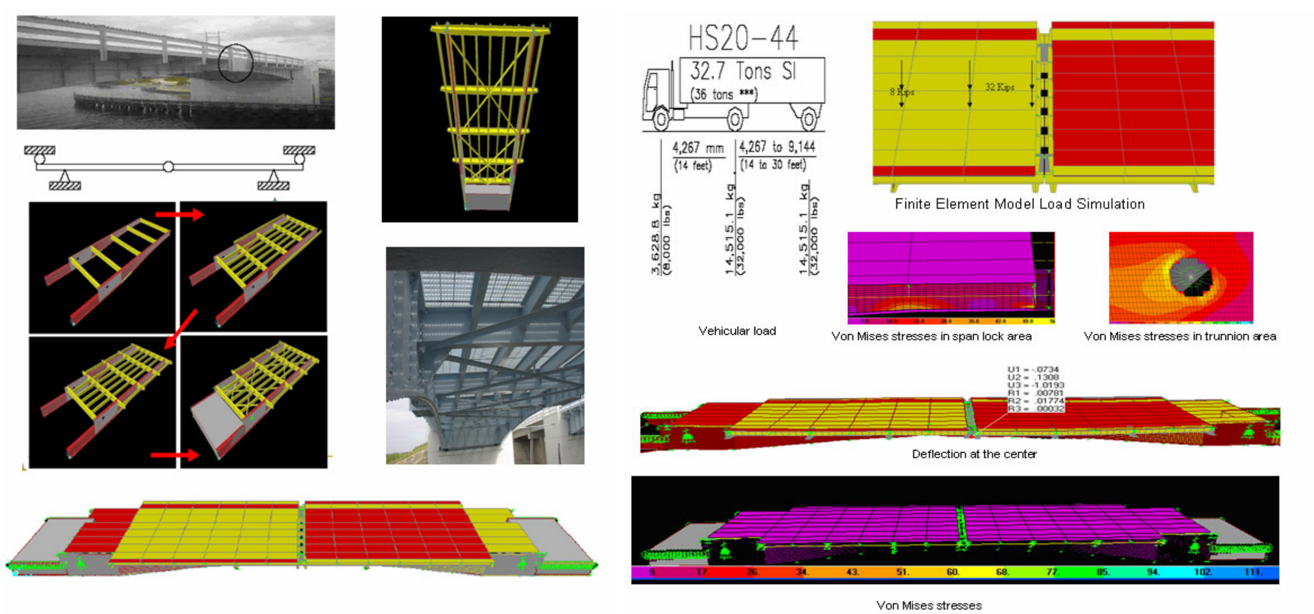


Figure 8. Finite element model for the case study

2.2. Instrumentation Plan

Based on the results obtained from the FE analysis, the following instrumentation plan was developed. Instrumentation of a draw-bridge is a very difficult task due to all mechanical/movable parts involved and the complexity of the mechanisms. Therefore, the instrumentation was limited to the sections and parts which are critical and whose malfunction would cause a catastrophic overall failure. Stresses caused by passing traffic will be monitored in correlation with the video images which will detect and classify the passing vehicle and correlate load with the response. The aerial video camera will be positioned as shown in Figure 9, and image processing algorithms will be working in real-time, synthesizing with the sensor data.

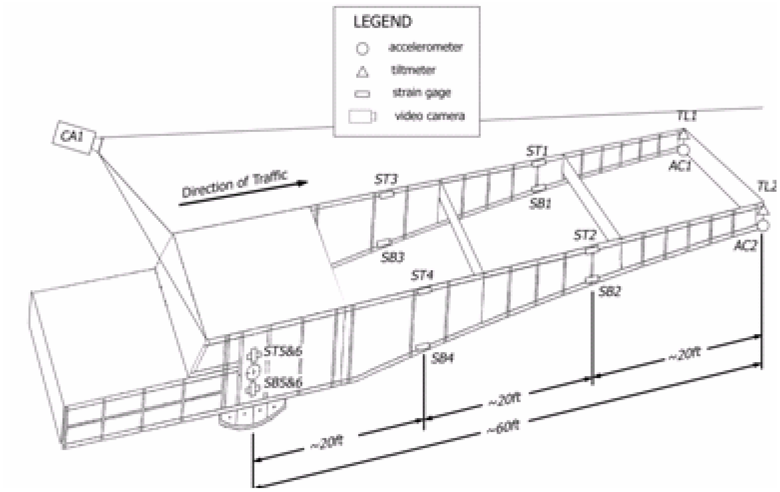


Figure 9. Instrumentation Plan for the Main Girders

2.3. Computer vision algorithms.

2.3.1. Moving Object Detection:

Identifying moving objects from a video sequence is a critical task for all vision systems. Some kind of mechanism is required to detect what is happening in the field of view of the camera. Any moving or out-of-place object becomes of interest and has to be somehow detected. Once objects are detected, further processing is needed to indicate in what direction the object is moving (tracking) and/or what type of object is (classification). In vision based systems a common approach to identifying the moving objects is background subtraction, where each video frame is compared against a reference or background model. Pixels in the current frame that deviate significantly from the background are considered to be moving objects and belonging to the foreground. This pixel based information is then clustered to identify regions, to label and classify objects. Computer vision techniques have been used especially for traffic monitoring and surveillance systems. The common approach for these methods consist of building a model of the scene background, and for each pixel in the image, detect deviations of feature values. Depending on the magnitude of this difference, pixels are classified either as belonging to the background or foreground. Although, pixel intensity or color are the most commonly used features for scene modeling, there are many others, and new approaches are been suggested periodically. Apart from the method used, all of them basically follow the scheme shown in Figure 10.

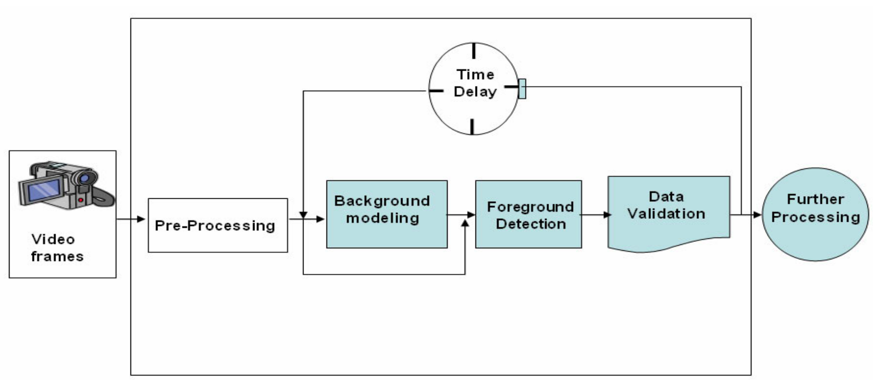


Figure 10. General Background Subtraction Method

For this particular research, objects were detected using background subtraction algorithm. A set of RGB video (99 frames) was used to create a background model, calculating the mean (Figure 11.a) and standard deviation (Figure 11.b) of every pixel/channel. Then, every new input frame (Figure 11.c) was compared against the model, normalizing the values according:

$$Change = \left\langle \begin{Bmatrix} Ir \\ Ig \\ Ib \end{Bmatrix} - \begin{Bmatrix} Mr \\ Mg \\ Mb \end{Bmatrix} \right\rangle x \frac{1}{\{\sigma r \quad \sigma g \quad \sigma b\}} x \langle \{Ir \quad Ig \quad Ib\} - \{Mr \quad Mg \quad Mb\} \rangle$$

After several trials, a threshold $\lambda = 1000$ was established as optimum. This means that if $Change \geq \lambda$, the new input pixel (Ir, Ig, Ib) is considered foreground otherwise is part of the background. This process gave as a result a binary image (video) where values of ‘1’ are assigned to the foreground and ‘0’ to the background, as showed in Figure 11.d.

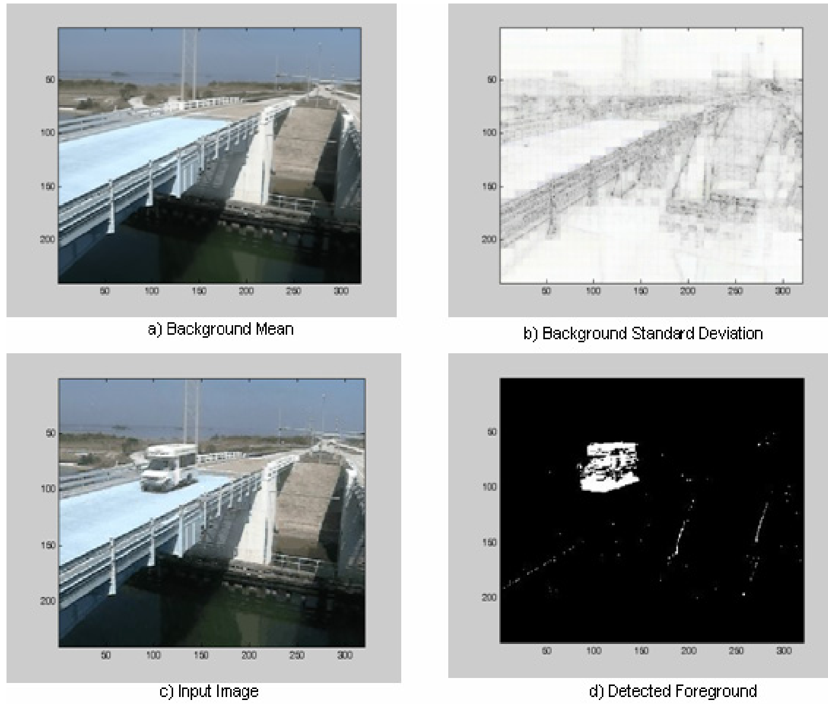


Figure 11 Background modeling and Foreground Detection

2.3.2. Data Validation:

Detection stage will include false positives appearing due to different reasons as background moving objects (leaves and branches, debris, shadows, occlusions, etc.) and, could lead to wrong results. Correlation between neighboring pixels and rate of adaptation is also important. To eliminate this false positives, data must be validated. The most common approach is to combine morphological filtering and connected components grouping to eliminate these regions.[7],[8],[9]. Morphological filters eliminate isolated foreground pixels and merges nearby disconnected foreground regions. Connected component grouping is used to identify all regions that are connected and eliminates those that are to small to correspond to real interest moving points. In this way, the remaining noise is eliminated (Figure 12).

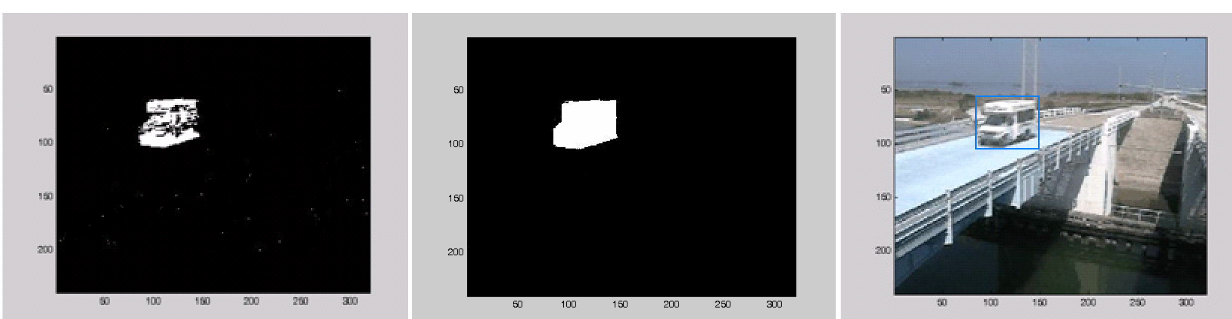


Figure 12. Results after applying noise reduction and connected components.

A bounding box was drawn around the object and, its size (number of pixels), centroid (location within the image) were calculated. Once each vehicle/object is detected and located in the image, the image coordinates have to be converted and mapped into the real world coordinates system. This was achieved by finding the intrinsic and extrinsic camera parameters that establish the relationship between image (I) and world (W) coordinates.

$$\begin{bmatrix} U_{image} \\ V_{image} \\ S \end{bmatrix} = \begin{bmatrix} -fk_x & 0 & o_x & 0 \\ 0 & -fk_y & o_y & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} r_{1,1} & r_{1,2} & r_{1,3} & t_x \\ r_{2,1} & r_{2,2} & r_{2,3} & t_y \\ r_{3,1} & r_{3,2} & r_{3,3} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_{world} \\ Y_{world} \\ Z_{world} \\ 1 \end{bmatrix}$$

These parameters were found by knowing a set of points in the image and real world, establishing a system of equations and using singular value decomposition to get the final solution.

2.3.3. Vehicle/object Tracking

A study was conducted on a real bridge for vehicle tracking. Moving objects in two consecutive frames were matched allowing the calculation of speed while moving along the bridge by using $v=d/t$ where v represents the speed, d is the distance between centroids of the same object for the two images, and t is the elapsed time between images (1/30 s. for two consecutive frames is the standard frame capture ratio for the type of camera used). To actually track a vehicle through the video, were used constraints like maximum speed, common motion, and minimum velocity. Additional information provided by color and size allowed to build an index weighted matrix which provided the most probable matching objects between the two frames. Estimation of the next position of the vehicle (centroid) was then found. This value is fundamental when correlating sensors readings and load positions.

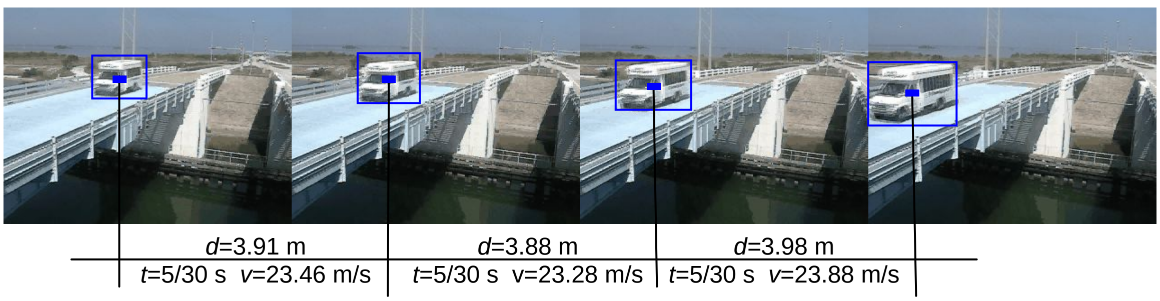


Figure 13. Results for tracking of a vehicle.

3. LABORATORY IMPLEMENTATION

Once the computer vision algorithms were tested on a real movable bridge, the researchers designed an experimental set-up to explore and demonstrate the integration of algorithms and technologies, as well as to find the best way to collect, process, and transmit the information. The set up consist of a two 10 ft. span structure conformed by a 1/8" steel deck 48 in. wide, supported by two HSS 25x25x3 girders separated 24 in. from each other. Supports were designed in such a way that could be easily changed to rolled, pinned or fixed boundary conditions as sown in Figure 15. Girder and deck can be linked together at different locations to modify the stiffness of the system and to simulate damage. Two radio controlled vehicles will crawl over the deck with different loading conditions (from 10lb. to 60 lb.). Wheel axis distance and speed are also variable. While a video camera is used to identifying the type of vehicle, a set of strategically located sensors will be collecting data to be correlated with the video stream in real-time.

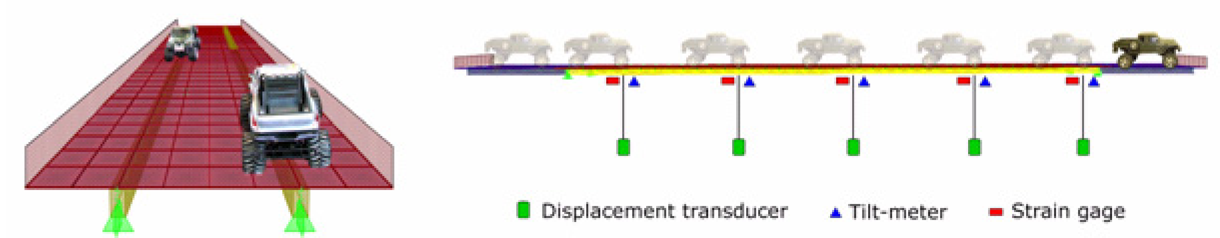


Figure 14. Finite element model for the experimental set-up.

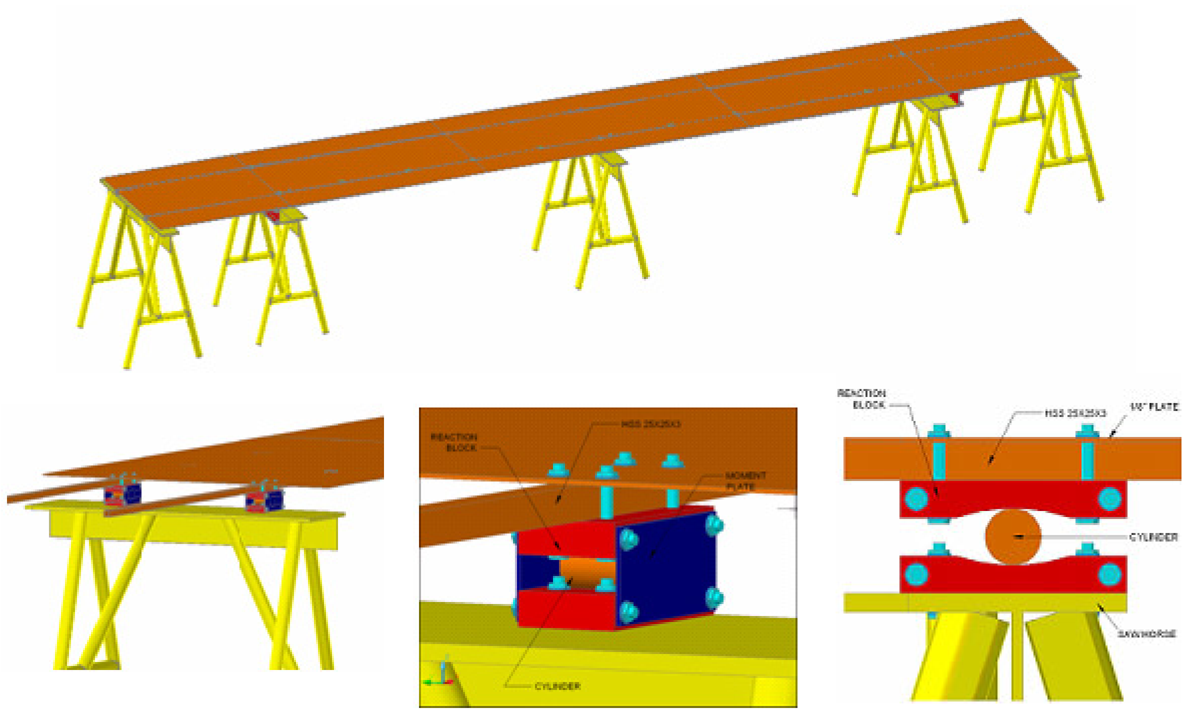


Figure 15. Experimental set-up details.

A FE model of the test set-up (Figure 14) was created to study the effects of the moving load regarding to deflection, rotation and strain at selected locations on the girders, as well as the dynamic properties of the structure. Some results of the simulation, shown in Figures 16 and 17, provide structural response data that will be employed in real life monitoring studies as well. More results and interpretations of these results will be presented at the conference by the writers.

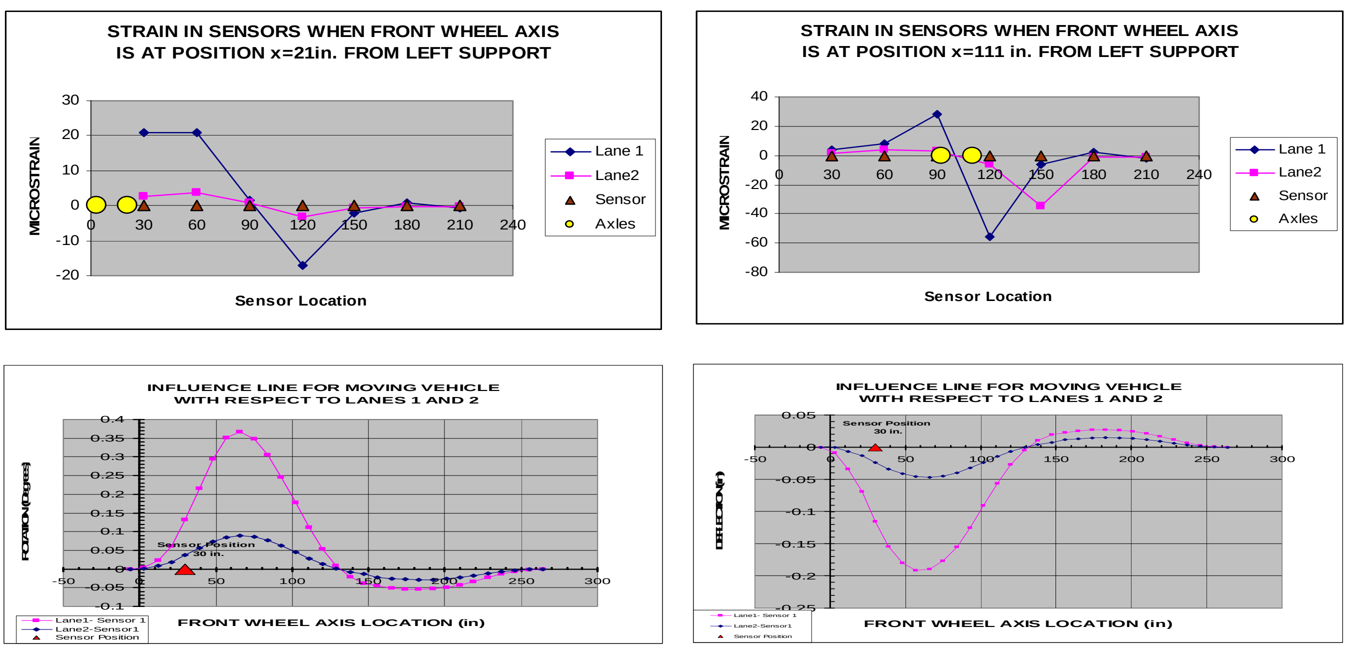
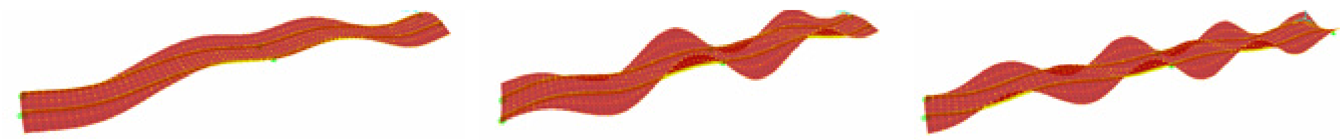


Figure 16. Some results: strain, rotation and deflection for the analyzed experimental set-up

Natural Frequency 1= 4.57 Hz. Natural Frequency 4 = 6.32 Hz. Natural Frequency 5 = 16.48 Hz.



Natural Frequency 8 = 17.95 Hz. Natural Frequency 15 = 25.44 Hz. Natural Frequency 24 = 33.19 Hz.

Figure 17. Some natural frequencies and mode shapes from the FEM for the experimental setup

4. CONCLUSIONS AND FUTURE WORK

The framework herein explained, represents a novel and practical technology where new approaches and techniques are used for Structural Health Monitoring. Real-time integration of computer vision techniques and sensing technology are studied with very promising results. In this paper, the writers first discussed the components of an integrated structural health monitoring system with special emphasis on computer vision aspects. The vision module will have detection, classification and tracking capabilities with unique problems when applied in real life operating bridges. These issues are discussed; solutions are proposed and demonstrated on a real bridge data. The writers are in the process of constructing a special structure in the laboratory to test their methods, algorithms, and to investigate the system integration before field deployment. The lab structure characteristics and sample data are also presented. From the practical point of view, the system will provide real-time continuous assessment, minimizing bridge's inspection costs and permanently tracking and recording the structural performance. This feature will improve safety and operational management, report of any abnormal behavior, generate image and numerical information with remote visual monitoring capability, and provide information for condition-based maintenance.

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