Exploring Indirect Vehicle-Bridge Interaction for Bridge SHM.

F. Cerda[1], J.Garrett, J. Bielak, R. Bhagavatula & J. Kovačević
Carnegie Mellon University, Pittsburgh, Pennsylvania, USA.

ABSTRACT: In this paper, we explore an indirect measurement approach for bridge structural health monitoring (SHM) that collects sensed information from the dynamic responses of many vehicles travelling over a bridge and then makes extensive use of advanced signal processing techniques to determine information about the state of the bridge. We refer to this approach as vehicle-data driven and indirect. We discuss some of the advantages of this indirect approach over direct monitoring of structures. We simplified the vehicle-bridge interaction and used a numerical oscillator-beam interaction model to generate some preliminary interaction response data with which to begin to assess the validity of this approach. A Multiresolution image classifier was used to analyze the preliminary data. We present the basic idea behind this approach and preliminary results that demonstrate its viability.

1 INTRODUCTION

1.1 *The Need for Structural Health Monitoring*

There are approximately 600,000 highway bridges within the U.S., and approximately 25 percent of them are currently rated as structurally deficient or functionally obsolete (Federal Highway Administration 2006)

Currently, bridges are inspected visually every two years. There is a strong interest to aid these inspection efforts with a more continuous, reliable, physics-based and less subjective procedure. This has led to a great deal of activity in structural health monitoring. Most of the current approaches consider data acquisition of bridges in a direct form, that is, by putting sensing devices at different specific locations on the structure. This poses a number of practical challenges, such as vandalism or involuntary damage of installed equipment, the need for a power source or complex energy harvesting, the initial and recurring costs associated with the monitoring system, and the need for extensive data processing and management at the bridge. Thus, there is an urgent need to explore alternative, more cost-effective means to monitor our complete stock of bridges on a regular basis.

[1] Also affiliated with the Universidad de Concepción, Concepción, Chile.

1.2 *Overview of Proposed Approach*

In this paper, we describe a possible approach for performing structural health assessment that takes a markedly different tack. This approach is based on the collection of, and multiresolution pattern analysis of, data in the form of dynamic responses of vehicles passing over bridge structures. This approach can be considered as indirect, since it acquires information about the bridge from sensor-equipped vehicles moving over the bridge, as described by Lin & Yang 2005. Since some bridges over which such vehicles travel will be monitored by sensor systems installed on the bridge, direct data gathered from the bridge itself can be used for validation and calibration of the vehicle-based monitoring system. Thus, this indirect approach can also be considered as complementary to the direct approach. The vehicle-based approach will allow for much broader coverage of the entire bridge population, as only a fraction of the bridges will likely by sensed directly due to initial and long-term maintenance costs of the installed monitoring systems.

The data will be acquired from many passing vehicles (cars, buses and trucks) that are able to timestamp and locate themselves with respect to the bridge and make that data available for structural analysis. The data can then be processed and analyzed with advanced signal processing and pattern recognition techniques, including state-of-the-art multiresolution techniques such as wavelets, to identify the existence, location and severity of damage. The idea is to infer damage from changes in global and local properties of the bridge and its structural response characteristics that are present in the vehicle dynamic response. Such structural response characteristics include resonant frequencies, mode shapes, local deflections, etc.

2 PROPOSED APROACH

As described in the previous section, our approach is based on merging two main concepts: 1) the sensed data will be collected from many vehicles moving over the structure of interest; and 2) the data will be collected and processed using advance image multiresolution techniques. We now present a more detailed discussion of the added features of this approach with respect to a direct monitoring approach. We start by reviewing some of the literature on direct approaches, some preliminary research on indirect approaches, the advantages of using an indirect monitoring approach, damage identification based on moving loads, the practical advantages of having mobile monitoring and a description of the multiresolution classifier.

2.1 *Direct Approaches for SHM*

During the past two decades, structural health monitoring and damage assessment have been very active research areas, and have motivated several excellent review and overview papers, which highlight some of the most relevant approaches (e.g., Van der Auweraer & Peeters 2003; Farrar & Worden 2007). Brownjohn (2006) describes some general and fundamental objectives for monitoring civil infrastructure and points out some historical applications. More specific review topics include wireless, structural health monitoring, design of devices, and the trend for localized processing (Lynch, 2007); vibration-based condition monitoring (Doebling et al. 1998, Carden & Fanning 2004); damage identification using inverse methods (Friswell 2006); unsupervised learning (Fulgate et al. 2000, Worden & Dulieu-Barton 2004, Worden & Manson 2007); and vibration-based condition monitoring methods (Carden & Fanning 2004).

One of the widely used classifications for structural health damage identification is based on the level of detection attempted (Rytter 1993): Level 1: determine presence of damage; Level 2: determine location of the damage; Level 3: quantify the severity of the damage; and Level 4: predict the remaining service life of the structure. A modification to these four levels, as described by Farrar & Worden (2007) considers the determination of the "type of damage" as an intermediate level between Levels 3 and 4. This incremental identification definition is suitable for the proposed approach, as it identifies the difficulty of detecting local failures.

Most of the existing literature addresses direct measurement approaches, in which sensors are placed on the structural elements from which one wishes to collect information to be used for the damage identification. The next section discusses research that has been done on indirect approaches to SHM, where data about the structure is collected from other sources, such as vehicles moving over the structure.

2.2 *Indirect Approaches for SHM*

Yang et al. presented an indirect approach in 2004, with the sole objective of extracting bridge frequencies from the dynamic response of a moving vehicle. They considered the bridge structure as a simply supported beam and the vehicle as a sprung mass. They derived an approximate analytical closed-form solution based only on the beam's first mode, and decoupled the bridge and the vehicle by neglecting the terms that contain the ratio of the oscillator mass to the beam total mass. This solution allows for the identification of a few significant dimensionless parameters that dominate the vehicle response, such as: $S = \pi v / L\omega_b$, a normalized vehicle velocity, where v = vehicle velocity, L = length of beam, and ω_b= bridge's natural fundamental frequency; and $\mu = \omega_b/\omega_v$, where ω_v is the vehicle (oscillator) vertical natural frequency. By performing a general finite element study, the concept was shown to be extendable to more complex structures. Later, Lin & Yang (2005) presented the experimental verification of the approach by using a four-wheel commercial light truck, towing a small two-wheel cart. They used accelerometers and velocity meters near the center of gravity of the cart to sense its vertical motion. The experiment also considered the use of a heavy truck that played the role of ongoing traffic. The authors concluded that it is feasible to scan the natural frequencies using the cart-based approach as the numerical study anticipated.

Another paper by Yang et al. (2005) explores the potential applications of an indirect approach to SHM. In this paper, Yang and his colleagues focused on the participation of the different modes of the bridges vibration and the complexity of dealing with multiple oscillators traveling at different speeds. The position of each vehicle within the bridge is crucial for determining the contribution of the different excitation sources (passing vehicles) to the dynamic response of the bridge when considering multiple oscillators. Yang et al. (2005) also concluded that the first mode of the bridge was dominant in the dynamic response.

Yang's promising idea was not used for damage detection, but only for extracting the natural frequencies of the structure. Moreover, work done by Farrar indicates that natural frequencies by themselves are not good damage predictors (Farrar & Jauregui1998). The study by Farrar consisted of experiments on the I-40 Bridge used to compare five different damage assessment methods against the same set of data in order to contrast their detection capability. Different levels of damage were inflicted to a girder to test the sensitivity of the five methods considered. The studies found that resonant frequencies and modal damping are insensitive to low levels of damage, but experimentally determined mode shapes are more sensitive indicators. They also found that changes caused by environmental conditions can be as significant as the ones caused by damage.

2.3 *Damage Identification Approaches Using Moving Oscillators as Excitation Sources*

We now briefly describe some of the research efforts regarding moving loads for damage detection and experimental validation. Law & Zhu (2004, 2005) explored the changes in different damage indicators and the possibility of capturing those changes when considering the excitation of a moving oscillator on a beam. The flexural stiffness has been used as a damage index measure that has a good correlation with a vehicle's response (Law & Zhu 2005). Other authors have presented a damage detection approach based on both the vehicle's and the bridge's response in the time domain (Majumber & Manohar 2003). Yet others report the dynamic response of damaged beams subjected to moving masses (Mahmoud & Abou Zaid 2002, Bilello & Bergman 2004), but these studies do not take into account the suspension system of a vehicle. This simplification can be well justified as dynamic response of the vehicle is far less important in terms of the overall load of the vehicle when considering a static and dynamic load separately. Experiments with moving masses over a sliding rail have been performed to validate mathematical models of damaged beams (Bilello & Bergman 2004).

2.4 *Practical Advantages of Indirect Measurements from Passing Vehicles*

In this section, we point out some of the issues that cause significant practical challenges for direct monitoring, which are absent or mitigated when using an indirect approach. Using an indirect approach to SHM will have a number of potential advantages.

The first issue is related to the powering of the sensors. Since direct monitoring requires that sensors be deployed on the bridge being monitored, there is a need to provide power for the sensors and their associated electronics and data transmission and storage devices. A sustainable approach to providing this will likely consider energy harvesting in various forms, such as optimized solar energy (Alippi & Galperti 2008) or vibration based power collection systems (Beedy et al. 2006). In the case of indirect monitoring, there is readily available energy from the vehicle's electric system that completely eliminates the concern for how to provide power to the sensors while the vehicle is in operation.

The useful life of structures is much greater than the current reliable lifespan of most sensors. An indirect monitoring approach mitigates this issue because it will use data collected from many passing vehicles, which will have a variety of ages and thus a variety of ages of their sensor systems. As vehicles are replaced, the sensors in them will be replaced as well. In addition, the sensors will be protected from environmental conditions and the threat of vandalism, and will be able to be evaluated on a regular basis during routine vehicle maintenance intervals, whereas direct measurement devices require costly onsite sensor maintenance and are subject to harsh environmental conditions and vandalism.

The indirect monitoring approach will not cause traffic interruption, nor require the use of artificial loading devices, such as shakers or controlled load trucks. We consider the many moving vehicles on the bridge as both the excitation and sensing source for the sensing system. The basic idea is that the vehicles collect information about the dynamic vehicle-bridge interaction as they drive on the bridge.

2.5 *Multiresolution Classification Approach*

The task of classification is a standard signal-processing task that involves assigning one of the possible classes to a given input signal. This is typically done by computing certain numerical descriptors, called features, on the given input, in the hope that these descriptors will be sufficient to discriminate among classes. For example, some of the commonly used features (and those we use in this work) are the Haralick texture features (Haralick et al. 1973). Thus, a generic classification system has a feature extraction block followed by a classifier block (see Figure 1).

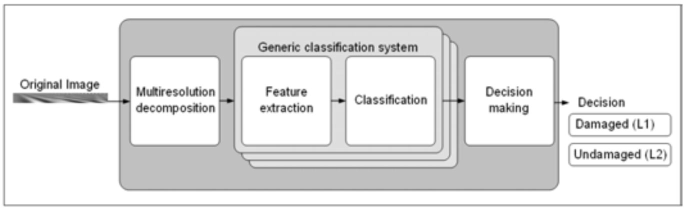

Figure 1. Multiresolution classification system for "Damaged" and "Undamaged" Labels.

Kovačević's lab has developed a new multiresolution classifier (Chebira et al. 2007c), that, instead of working on the original signal, passes it first through a multiresolution decomposition block generating a number of smaller-size signals, called subbands, in different subspaces. These subbands then each undergo separate classification, generating their own local classification decisions. In other words, each of the subbands is classified, each representing a possible classification of the actual signal. To reconcile these different possible classifications, the decision making block arbitrates and decides on the final label. This arbitration can be in closed form (that is, a solution to a least squares problem is found) or open form (where a reward-punishment system is iteratively applied onto subband local decisions). There can be as many labels as desired to take into account the different levels of damage identification. Considering the idea of *Existence*, Level 1 of damage identification, classifying signals as being "Damaged" and "Undamaged" (Figure 1) is the first experiment presented later in this paper.

In the research presented, synthetic data was created that would enable testing of the classification capability of the multiresolution algorithm for our application. The vehicle response vertical acceleration data was generated using a simplified numerical oscillator-beam interaction model that we describe below.

3 OSCILLATOR-BEAM INTERACTION MODEL

To explore the feasibility of this approach, an oscillator-beam interaction (OBI) model was implemented. It considers the coupling of the oscillator and the beam at a regular interval, ΔT. The algorithm iterates until the deflection of the beam at the point of interaction (z_b) and the base degree of freedom of the oscillator (z_v) converge. Only a few iterations are needed. Figure 2 shows a scheme of the implemented model.

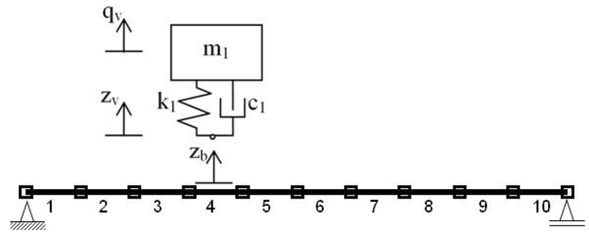

Figure 2. Oscillator beam model.

The model was validated against the results reported by Yang et al. (2004). For the experiments we chose oscillators of three different vertical fundamental frequencies (1.1, 1.7, and 3.4 Hz) to represent a small vehicle, large family vehicle and a truck, respectively. In addition, 30% critical damping was assumed for the different oscillators for modeling the shock absorbers and other energy dissipation in the vehicle. The beam is an idealization of a 40-m bridge, I=0.219 m^4 (Kim & Kawatani 2008) and it is discretized into 10 finite elements.

With some small changes to this numerical model, as described in the following list, we were able to produce synthetic response data for different damage conditions, such as:

a. *distributed section loss*, such as that caused by corrosion, and modeled by a percent reduction of the moment of inertia of a beam finite element;
b. *a section crack*, such as that caused by fatigue in steel elements, and modeled as a rotational spring, where the spring stiffness depends on the crack depth being modeled; and
c. *frozen bearings of bridge supports*, modeled using rotational spring elements linked to the rotational degrees of freedom at the ends of the beam.

The location and severity of these three damage conditions can be easily altered within the modeled beam. This allows a large number of different damage cases and associated response signals to be generated. In the research reported here, we first tested the ability of the approach to detect the absence or presence of section loss in different elements, and then considered an example in which different levels of damage were present.

4 MULTIRESOLUTION CLASSIFICATION

We now give a brief overview of the multiresolution techniques and wavelet-based approach we are using. Multiresolution techniques have been extensively studied and used in signal and image processing over the past two decades (Daubechies 1992, Vetterli & Kovačević 1995, Mallat 1999). We call multiresolution techniques those signal processing tools that analyze and process signals across different frequency resolutions and scales. They have arisen in response to the inability of some standard techniques, such as Fourier analysis, to deal with nonstationary signals. For example, abrupt transitions in time cannot be captured using Fourier methods. An easy analogy is that with map programs on the Web, such as Google Maps. If we are looking into how to get to New York from Boston, the initial route will be at the scale/resolution of 50 km/1 in. Once close to New York, we will want more detailed directions, say to the Museum of Natural History, and would thus move to a scale/resolution of 2000 ft/1 in, which is the street level. In other words, we first investigated the global behavior of our signal, followed by its local behavior at a certain scale. This approach can be used in any situation where the signal is nonstationary. For example, we may assume that the data collected from a vehicle on a bridge will differ depending on time of day, day of the year, season, and many other factors. This is one of the main advantages of using this approach, as it enables the classification of new data based on a baseline provided by previous records. It takes into account modifications of the response by various factors, such as seasonal changes or daily temperature variations, as long as sufficient data is available.

The multiresolution techniques achieve their goal by decomposing a signal into zooming spaces (e.g., coarse subspaces and detailed subspaces) and are implemented by a signal-processing device called a filter bank. This filter bank then implements a specific multiresolution transform. Some well-known transforms that fit within this framework are the discrete Fourier transform (DFT) and the discrete cosine transform (DCT). Others, originating in the multiresolution literature, are the discrete wavelet transform (DWT) and a family of wavelet packet (WP) transforms. Which one of these to use depends on the specific application at hand. For more details, see, for example, Vetterli & Kovačević (1995).

One possible characterization of multiresolution transforms is in terms of whether they represent the signal in a nonredundant or a redundant fashion. Redundancy often leads to increased accuracy, as has been found in a host of bioimaging problems (see Chebira & Kovačević 2008a and references therein). One possible example of the power of multiresolution techniques in pattern classification is that developed for the classification of Drosophila embryo development (Kellogg et al. 2007). Using a highly accurate multiresolution classification algorithm developed by Kovačević and her group, the process is now automated and reproducible, with accuracy greater than 98% (Kellogg et al. 2007).

The use of wavelets in structural damage identification is relatively new. Melhem & Kim (2003) used continuous wavelet transform and Fourier analysis to detect damage on two full-scale concrete structures (a prestressed beam and pavement on grade) subjected to fatigue loads. Acceleration and deflection measurements were taken directly from the beam. Differences between initial and final damage states were significant and the wavelet analysis allowed for the identification of damage progression on both of the studied structures. Another study by Sun & Chang (2004) used a statistical wavelet-based method for structural health monitoring, which considered progressive damage on a steel cantilever beam. Sun concluded that indicators from the Wavelet Packet Signature (WPS) are excellent indicators for monitoring structural health condition. They are sensitive to structural damage and insensitive to measurement noise.

A recent paper by Law et al. (2008) makes use of wavelet transforms for identifying a moving load over a beam and the prestress condition. In Law's work, the measuring points are located at the bottom of the beam. The forces of two moving axles and the prestress levels are identified successfully over time with high accuracy.

4.1 *Multiresolution Algorithm for Classifying Signals from the OBI Model*

The multiresolution classifier we use here was originally developed for images. For the purpose of testing whether it would make sense to use it for classifying the signals taken from a vehicle moving over a bridge, we had to produce images from the collected vehicle data. This requires the images to be at the same scale, considering the maximum and minimum values of the whole set of data as the scale limits. As an example, Figure 3 shows an image before scaling. It corresponds to a 2% inertia reduction on an element adjacent to the midspan of the beam. The ordinate represents the different velocities of the oscillator, and the abscissa refers to the relative position of the oscillator with respect to the beam. The colors represent the acceleration value of the oscillator. The scale and frequency content of the image represent the dependency of the response on the position and velocity of the oscillator.

At Level 1, the multiresolution decomposition takes an image and produces a number of smaller images from which the original one can be reconstructed, if needed (see Figure 4). At Level 2, the same, or different, multiresolution decomposition is applied to a subset, or all, of the images from Level 1. The process can be repeated many times, at each level producing subbands at a different resolutions/scales. For example, Figure 4 shows a preprocessed scaled input image, and four subbands at Level 1. In our experiments we used a 2-level full decomposition (meaning at each level, each subband is split into four subbands at the next level). The left-most subband is typically the one that carries the global characteristics of the signal (so it very much looks like the higher-level image, but blurred), while the other three carry the necessary details to reconstruct the original (these are the local changes, or, edges).

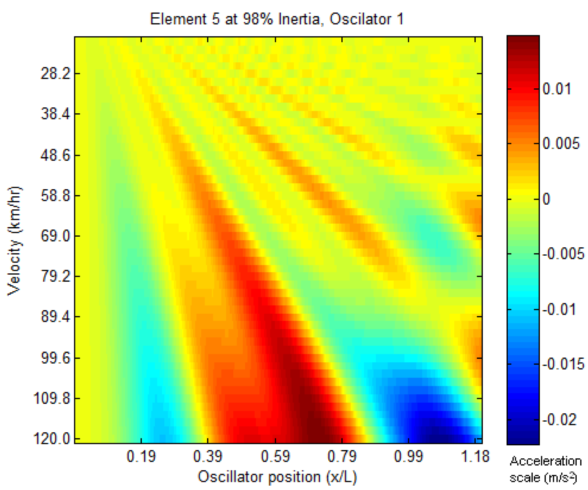

Figure 3. Raw image representation of acceleration response of traveling oscillator.

When small amounts of data are available, as is the case here, a technique called *leave-one-out cross validation (LOOCV)* is used. LOOCV attempts to estimate the generalization error of the classifier, which is effectively the capability of the classifier to correctly classify unseen data (i.e., data that has not been trained on). Let N be the number of data samples, $[x_1\ x_2\ \ldots\ x_N]$, for a particular class of images to be classified. For a particular data sample x_i, the classifier is trained using samples $[x_1\ \ldots\ x_{i-1}\ x_{i+1}\ \ldots\ x_N]$ and is tested over the sample x_i. This is repeated for each available data sample that results in N separate classifiers being trained and tested. The overall accuracy of the classifier is the average accuracy over these N results.

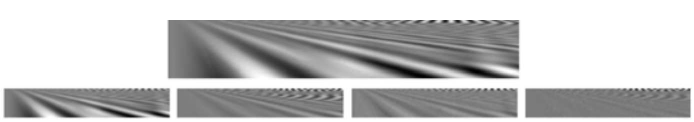

Figure 4. Multiresolution decomposition (Level 1). Preprocessed original image (top); four subbands (bottom).

4.2 *Experimental Setup and Results*

We conducted two experiments with the acceleration response of the oscillators obtained from the numerical model described in Section 3.

Experiment 1: Existence of damage classification. In this experiment, we attempted to classify the bridge into one of two categories: "Undamaged" (5 cases, Table 1); or "Damaged" (Levels 1-4 lumped together, 25 cases, Table 1). Thus, with N=30, there were 30 two-class classification experiments for each of the three oscillators and each of the 10 elements.

Table 1. Damage cases considered.

Label	Damage range [%]	# of cases
Undamaged	0-4	5
Level 1	5-9	5
Level 2	10-14	5
Level 3	15-29	8
Level 4	30-55	7

Table 2 shows the overall classification accuracy for the "Undamaged" and "Damaged" cases over each element. These results indicate that this approach is able to achieve very high accuracy in classifying a damage condition occurring over an element near the midspan for the three oscillators.

Table 2. Two-class damage classification accuracy (in %).

Element	Oscillators			**Accuracy**
	1.1Hz (small veh.)	1.7 Hz (family veh.)	3.2Hz (truck)	
1	96.7	83.3	76.7	**85.6**
2	76.7	86.7	73.3	**78.9**
3	96.7	86.7	86.7	**90.0**
4	93.3	93.3	96.7	**94.4**
5	93.3	93.3	96.7	**94.4**
6	100.0	90.0	100.0	**96.7**
7	93.3	93.3	80.0	**88.9**
8	83.3	90.0	90.0	**87.8**
9	83.3	86.7	73.3	**81.1**
10	90.0	83.3	83.3	**85.5**
Accuracy	**90.7**	**88.7**	**85.7**	**88.4**

Note that the first oscillator achieves the highest average accuracy, followed by the second and then the third. One might infer that the larger the load, the lower the accuracy. These results are preliminary because they use a highly idealized beam to represent a bridge. We must run more experiments involving structures with different natural frequencies and different vehicles to validate this conjecture. Also, in this experiment, it was possible to determine the damage in some elements very accurately (for example, Element 6), while not for others (for example, Element 2 near the end of the beam). Overall, the multiresolution classification approach achieved an average accuracy of 88.4% in determining the *existence* of damage. We are thus encouraged that a more comprehensive investigation of this approach will improve these accuracies.

Experiment 2: Severity of damage classification. This experiment considers an undamaged class and four damage levels for a total of five classes/labels as described in Table 1. With these five labels, there were again N=30 classification experiments, but there were five classes to be distinguished for each oscillator and element. Table 3 shows the overall classification accuracy for the five classes ("Undamaged" and "Damaged" levels 1-4) for each oscillator and beam element. The results shown in Table 3 can be read as: the percentage of accuracy to classify an image representation (see Figure 3) of the vehicle response as a specific damage level (Table 1), on a particular element and considering a particular vehicle. Note that what is reported in the table is the aggregate accuracy of the methodology for distinguishing each of the five levels of damage.

First, observe that, as expected, the accuracies in Experiment 2 are lower compared to those from Experiment 1. This is because it is harder, using the same number of actual collected signals, to distinguish between five different levels of damage, as opposed to just the undamaged/damaged situations. In contrast to Experiment 1, the middle oscillator gives the most accurate results in Experiment 2. Overall, the multiresolution approach achieved an average accuracy of 71.2% in determining the severity of the damage.

Table 3 Five-class severity of damage classification accuracy (in %).

Element	Oscillators			**Accuracy**
	1.1Hz (small veh.)	1.7 Hz (family veh.)	3.2Hz (truck)	
1	66.7	80.0	83.3	**76.7**
2	66.7	76.7	66.7	**70.0**
3	80.0	73.3	40.0	**64.4**
4	60.0	66.7	70.0	**65.6**
5	76.7	80.0	63.3	**73.3**
6	76.7	80.0	73.3	**76.7**
7	76.7	73.3	70.0	**73.3**
8	73.3	66.7	50.0	**63.3**
9	66.7	83.3	66.7	**72.2**
10	73.3	80.0	76.7	**76.7**
Accuracy	**71.7**	**76.0**	**66.0**	**71.2**

5 CONCLUSIONS

We have presented an alternative approach for indirect monitoring of the structural health of bridges through data collected from vehicles passing over a bridge. To test the validity of this approach, we created a numerical model of the interaction between a simple oscillator and a simple beam and subjected the beam to different levels of section loss at different locations. We then subjected the simulated responses to these damaged states to a multiresolution classification system in order to determine how accurately the damage level could be classified. The results of these two experiments, while limited and very preliminary, seem promising. We are encouraged to further pursue the refinement and evaluation of this approach.

6 AKNOWLEDGEMENTS

Financial support for this research from the following sources is gratefully acknowledged: 1) The Fulbright Foundation-MECESUP2 scholarship, Gobierno de Chile; 2) Professor Pradeep Khosla, Dean of the College of Engineering, Carnegie Mellon; 3) Dr. Richard McCullough, Vice President of Research, Carnegie Mellon University; 4) the Hillman Foundation.

7 REFERENCES

Alippi, C., and Galperti C. 2008. An Adaptive System for Optimal Solar Energy Harvesting in Wireless Sensor Network Nodes. *Circuits and Systems* I: Regular Papers, IEEE Transactions on 55, no. 6: 1742-1750.

Beeby, S. P., Tudor, M. J., & White N. M. 2006. Energy harvesting vibration sources for microsystems applications. *Measurement Science and Technology* 17, no. 12: R175-R195.

Bilello, C., & Bergman L. A. 2004. Vibration of damaged beams under a moving mass: theory and experimental validation. *Journal of Sound Vibration* 274 (Jul 1): 567-582.

Brownjohn, J.M.W. 2007. Structural health monitoring of civil infrastructure. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 365, no. 1851 (February 15): 589-622.

Carden, E. P., & Fanning P. 2004. Vibration Based Condition Monitoring: A Review. *Structural Health Monitoring* 3, no. 4 (December 1): 355-377.

Chebira, A. & Kovačević, J. 2007. Adaptive multiresolution frame classification of biological and biometric images. *Proc. of SPIE Conf. on Wavelet Applications in Signal and Image Proc.*, San Diego, USA, Aug.

Chebira, A., Coelho, L. P., Sandryhaila, A., Lin, S., Jenkinson, G. W., MacSleyne, J., Hoffman, C., Cuadra, P., Jackson, C., Püschel, M., & Kovačević, J. 2007a An adaptive multiresolution approach to fingerprint recognition," *Proc.*

IEEE Conf. on Image Proc., San Antonio, TX, Sep. pp. I:457–460.

Chebira, A. & Kovačević, J. 2007b. Lapped tight frame transforms. *Proc. IEEE Int. Conf. Acoust., Speech, and Signal Proc.*, Honolulu, HI, Apr. pp. III:857-860.

Chebira, A., & Kovačević, J. 2008a. Frames in bioimaging. Proc. CISS, Princeton, NJ, Mar.

Chebira, A., Ozolek, J. A., Castro, C. A., Jenkinson, W. G., Gore, M., Bhagavatula, R., Khaimovich, I., Ormon, S. E., Navara, C. S., Sukhwani, M., Orwig, K. E., Ben-Yehudah, A., Schatten, G., Rohde, G. K., & Kovačević, J. 2008b. Multiresolution identification of germ layer components in teratomas derived from human and nonhuman primate embryonic stem cells. *Proc. IEEE Intl. Symp. Biomed. Imaging*, Paris, France, May. pp. 979-982.

Chebira, A., Barbotin, Y., Jackson, C., Merryman, T., Srinivasa, G., Murphy, R. F., & Kovačević, J. 2007c. A multiresolution approach to automated classification of protein subcellular location images. *BMC Bioinformatics*, vol. 8, no. 210.

Daubechies, I. 1992. Ten lectures on wavelets. Society for Industrial and Applied Mathematics.

Doebling, S. W, Farrar C. R, & Prime M. B.. 1998. A summary review of vibration-based damage identification methods. Identification Methods," *The Shock and Vibration Digest* 30: 91-105.

Farrar, C. R., & Jauregui, D. A. 1998. Comparative study of damage identification algorithms applied to a bridge: I. Experiment.*Smart Materials and Structures* 7, no.5:704-719.

Farrar, C. R., & Worden K. 2007. An introduction to structural health monitoring. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 365, no. 1851 (February 15): 303-315.

Federal Highway Administartion 2006. Status of the Nation's Highways, Bridges and Transit: Conditions and Preformance. http://www.fhwa.dot.gov/policy/2006cpr

Friswell, M. I. 2007. Damage identification using inverse methods. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 365, no. 1851 (February 15): 393-410.

Fugate, M. L., Sohn H., & Farrar C. R. 2000. Unsupervised learning methods for vibration-based damage detection. *Presented at IMAC*, San Antonio, Texas. February 7-10.

Haralick, R.M, K. Shanmugan, and I. Dinstein. 1973. Textural features for image classification. EEE Trans. on Systems, Man, and Cybernetics 3, no. 6: 610-621.

Kellogg, R. A., Chebira, A., Goyal, A., Cuadra, P. A., Zappe, S. F., Minden, J. S., & Kovačević, J. 2007. Towards an image analysis toolbox for high-throughput Drosophila embryo RNAi screens. *Proc. IEEE Intl. Symp. Biomed. Imaging*, Arlington, VA, Apr. pp. 288-291.

Kim, C. W, & Kawatani M.. 2008. Pseudo-static approach for damage identification of bridges based on coupling vibration with a moving vehicle. *Structure and infrastructure engineering* 4, no. 5: 371-379.

Law, S. S, & Zhu. X. Q. 2005. Nonlinear characteristics of damaged concrete structures under vehicular load. *Journal of Structural Engineering-ASCE* 131, no. 8 (August): 1277-1285.

Law, S. S., Wu S. Q., & Shi Z. Y. 2008. Moving Load and Prestress Identification Using Wavelet-Based Method. *Journal of Applied Mechanics* 75, no. 2 (Mar. 0): 021014-7.

Law, S. S., & Zhu X. Q. 2004. Dynamic behavior of damaged concrete bridge structures under moving vehicular loads. *Engineering Structures* 26, no. 9 (July): 1279-1293.

Lin, C.W., & Yang Y.B. 2005. Use of a passing vehicle to scan the fundamental bridge frequencies: An experimental verification. *Engineering Structures* 27, no. 13 (November): 1865-1878.

Lynch, J. P. 2007. An overview of wireless structural health monitoring for civil structures. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 365, no. 1851 (February 15): 345-372.

Mahmoud, M. A., & Abou Zaid M. A.. 2002. Dynamic response of a beam with a crack subject to a moving mass. *Journal of Sound and Vibration* 256, no. 4 (September 26): 591-603.

Majumder L., & Manohar C. S. 2003. A time-domain approach for damage detection in beam structures using vibration data with a moving oscillator as an excitation source. *Journal of Sound and Vibration* 268, no. 4 (December 4): 699-716.

Mallat, S. 1999. A Wavelet Tour of Signal Processing. 2nd ed. Academic Press.

Melhem, H., & Kim H. 2003. Damage Detection in Concrete by Fourier and Wavelet Analyses. *Journal of Engineering Mechanics* 129, no. 5 (May 0): 571-577.

Rytter, A, 1993. Vibration based inspection of civil engineering structures. *Department of Building Technology and Structural engineering, Aalborg University*, Denmmark.

Sun, Z., & Chang, C. C. 2004. Statistical Wavelet-Based Method for Structural Health Monitoring. *Journal of Structural Engineering* 130, no. 7 (July 0): 1055-1062.

Van der Auweraer, H., & Peeters B.. 2003. International Research Projects on Structural Health Monitoring: An Overview. *Structural Health Monitoring* 2, no. 4 (December 1): 341-358.

Vetterli, M. & Kovačević, J. 1995. Wavelets and Subband Coding, Prentice Hall, Signal Processing Series, Englewood Cliffs, NJ.

Worden, K., &. Dulieu-Barton J. M. 2004. An Overview of Intelligent Fault Detection in Systems and Structures. *Structural Health Monitoring* 3, no. 1 (March 1): 85-98.

Worden, K., & Manson G. 2007. The application of machine learning to structural health monitoring. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 365, no. 1851 (Feb. 15): 515-537.

Yang, Y. B., Lin C. W., & Yau J. D. 2004. Extracting bridge frequencies from the dynamic response of a passing vehicle. *Journal of Sound and Vibration* 272, no.3-5(May 6):471-493.

Yang, Y.B., & Lin C.W. 2005. Vehicle-bridge interaction dynamics and potential applications. *Journal of Sound and Vibration* 284, no. 1-2 (June 7): 205-226