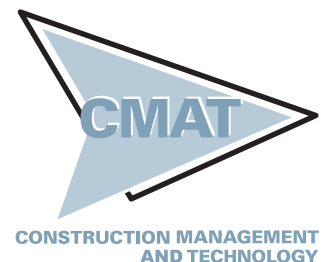


# Terrestrial Laser Scanning-Based Bridge Structural Condition Assessment

**Final Report**  
**May 2016**



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Midwest Transportation Center  
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# **TERRESTRIAL LASER SCANNING-BASED BRIDGE STRUCTURAL CONDITION ASSESSMENT**

**Final Report  
May 2016**

**Principal Investigator**

Yelda Turkan, Assistant Professor  
Construction Management and Technology Program  
Institute for Transportation, Iowa State University

**Co-Principal Investigator**

Simon Laflamme, Assistant Professor  
Civil, Construction, and Environmental Engineering, Iowa State University

**Research Assistant**

Liangyu Tan

**Authors**

Yelda Turkan, Simon Laflamme, and Liangyu Tan

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A report from  
**Institute for Transportation**  
**Iowa State University**  
2711 South Loop Drive, Suite 4700  
Ames, IA 50010-8664  
Phone: 515-294-8103  
Fax: 515-294-0467  
[www.intrans.iastate.edu](http://www.intrans.iastate.edu)



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## **EXECUTIVE SUMMARY**

Objective, accurate, and fast assessment of a bridge's structural condition is critical to the timely assessment of safety risks. Current practices for bridge condition assessment rely on visual observations and manual interpretation of reports and sketches prepared by inspectors in the field. Visual observation, manual reporting, and interpretation have several drawbacks, such as being labor intensive, subject to personal judgment and experience, and prone to error.

Terrestrial laser scanners (TLS) are promising sensors for automatically identifying structural condition indicators, such as cracks, displacements, and deflected shapes, because they are able to provide high coverage and accuracy at long ranges. However, limited research has been conducted on employing laser scanners to detect cracks for bridge condition assessment, and the research has mainly focused on manual detection and measurement of cracks, displacements, or shape deflections from the laser scan point clouds.

This research project proposed to measure the performance of TLS for the automatic detection of cracks for bridge structural condition assessment. Laser scanning is an advanced imaging technology that is used to rapidly measure the three-dimensional (3D) coordinates of densely scanned points within a scene. The data gathered by a laser scanner are provided in the form of point clouds, with color and intensity data often associated with each point within the cloud. Point cloud data can be analyzed using computer vision algorithms to detect cracks for the condition assessment of reinforced concrete structures. In this research project, adaptive wavelet neural network (WNN) algorithms for detecting cracks from laser scan point clouds were developed based on the state-of-the-art condition assessment codes and standards. Using the proposed method for crack detection would enable automatic and remote assessment of a bridge's condition. This would, in turn, result in reducing the costs associated with infrastructure management and improving the overall quality of our infrastructure by enhancing maintenance operations.

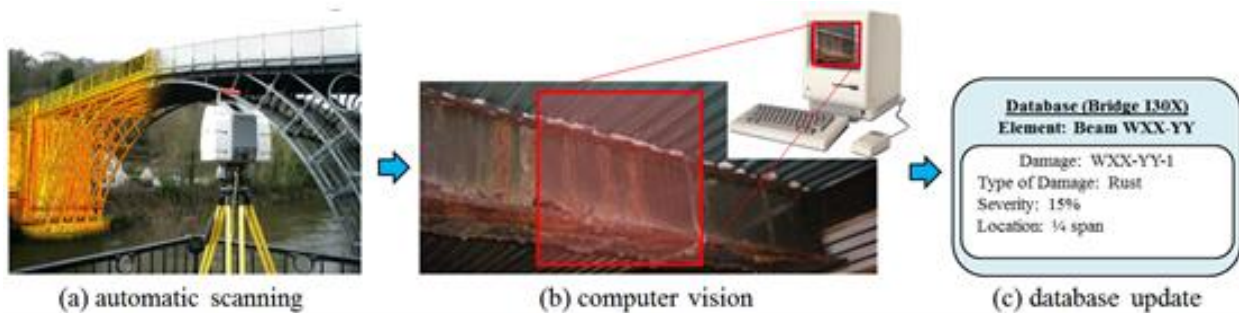


## INTRODUCTION

The majority of bridge condition assessments in the US are conducted by visual inspection, in which a printed checklist is filled out by structural engineers or trained inspectors. An inspector must correctly identify the type and location of each element being inspected, document its distress, manually record this information in the field, and then transcribe that information to the bridge evaluation database after arriving back at his/her office. This is a complex and time-consuming set of responsibilities, which are prone to error.

Terrestrial laser scanners are promising sensors for documenting the as-built condition of infrastructure (Hajian and Brandow 2012), and they have already been utilized by a number of state departments of transportation (DOTs) for this purpose in the project planning phase. Furthermore, terrestrial laser scanning (TLS) technology has been shown to be effective in identifying structural condition indicators, such as cracks, displacements, and deflected shapes (Park et al. 2007, Olsen et al. 2009, Werner and Morris 2010, Meral 2011, Wood et al. 2012), because they are able to provide high coverage and accuracy at long ranges. However, limited research has been conducted on employing laser scanners to detect cracks for bridge condition assessment (Chen 2012, Chen et al. 2012, Olsen et al. 2013).

This research project investigated the performance of TLS for detecting cracks automatically for bridge structural condition assessment (Olsen et al. 2009, Anil et al. 2013, Adhikari et al. 2013, Mosalam et al. 2013). TLS is an advanced imaging technology that is used to rapidly measure the three-dimensional (3D) coordinates of densely scanned points within a scene (Figure 1(a)).



**Figure 1. Research vision**

The data gathered by a TLS is provided in the form of 3D point clouds, with color and intensity data often associated with each point within the cloud. Point cloud data can be analyzed using computer vision algorithms (Figure 1(b)) to detect structural conditions (Figure 1(c)).

### Relevance to MTC Theme and Thematic Thrust Areas

The Midwest Transportation Center (MTC) theme is Data-Driven Performance Measures for Enhanced Infrastructure Condition, Safety, and Project Delivery. The proposed TLS-based structural condition assessment method enables automated and remote condition assessment of

reinforced concrete structures. The proposed method would (1) enhance infrastructure condition by enabling a more efficient and accurate structural condition assessment, (2) improve safety by reducing the time spent in the field on manual data collection, and (3) improve project delivery by enabling structural condition data to be stored electronically, which would make the data much easier to retrieve and to maintain than in a conventional paper-based document management system.

## **LITERATURE REVIEW**

Visual inspection is the most conventional and widely used method for crack detection in bridge condition assessment. However, many researchers have proposed and developed several contact and non-contact techniques for crack detection on concrete and steel surfaces. Contact techniques are those techniques that require physical contact between the instrument/tool and the entity of interest for the purpose of detecting cracks. Non-contact techniques are those techniques that are independent of any physical contact. This section provides a review of previous studies on contact and non-contact inspection techniques, terrestrial laser scanning technology, and point cloud processing using adaptive wavelet neural networks (WNNs).

### **Non-Contact Techniques for Crack Detection**

Several crack detection algorithms to process the data collected using non-contact techniques have been proposed and used in the last two decades. A study comparing traditional and neural network classifiers was conducted by Kaseko et al. (1994) for detecting defects on asphalt concrete pavements. An image-based crack detection algorithm was developed to inspect aircraft surfaces (Siegel et al. 1997). To be able to detect cracks, the proposed algorithm detected rivets because cracks propagate on rivet edges, and then multi-scale edge detection was used to detect the edges of small defects at small scales and the edges of large defects at larger scales.

Dare et al. (2002) proposed a technique for crack detection based on semi-automatic feature extraction. In this study, the authors used bilinear interpolation of pixel values to calculate the crack width. The measurements were made in pixels, not in unit length. Ito et al. (2002) proposed a crack area quantification technique, which involved an interpolation method based on the total brightness of grayscale images. A scale parameter was implemented to convert crack dimensions originally obtained in pixels to SI units. This approach was further improved by Yamaguchi and Hashimoto (2010), who proposed an edge information and percolation model-based crack detection approach.

Sohn et al. (2005) proposed a system for monitoring crack growth, which focused on detecting newly generated cracks with the help of spatiotemporal images. This study did not quantify crack width and orientation. Abdel-Qader et al. (2003) compared and analyzed the efficiency of four different edge detection techniques for identification of cracks on concrete bridges. The study concluded that the Fast Haar Transform (FHT) is the most effective edge detection method for crack detection on concrete surfaces when compared to the Fast Fourier Transform (FFT), Canny, and Sobel methods.

### **Contact Techniques for Crack Detection**

A number of contact techniques have been proposed by several researchers to detect and monitor crack development on conductive concrete surfaces. Pour-Ghaz and Weiss (2011) introduced a technique to monitor cracks based on the electrical resistance of a conductive thin film applied to the surface of a cement material. In this method, the time and location of the crack are measured

by monitoring abrupt increases in the resistance of the conductive surface coating. However, separate data acquisition channels are required for each component when using conductive surface components. Pour-Ghaz and Weiss (2011) solved this problem by developing a frequency selective circuit (FSC) in which numerical methods were used to analyze the response of the FSC for the fast and synchronized interrogation of the multiple conductive surface elements.

In order to automate the process of structural assessment, especially for concrete, a number of sensor-based approaches have been proposed by several researchers. Ouyang et al. (1991) and Shah and Choi (1999) developed a crack detection method by capturing stress waves generated by cracks in concrete elements. This technique was based on piezoelectric sensors employing acoustic emission, which can be categorized under passive stress wave methods. Carino (2004) developed pulse-echo and pitch-catch methods, which required using one and two transducers, respectively, to categorize cracks on actual concrete elements. This technique can be subcategorized under active stress wave methods, which are more accurate for crack detection purposes. Overall, contact techniques for crack detection are fairly accurate. However, they require employing different sensing tools that increase the overall lifecycle costs of the structure under inspection. Moreover, these techniques require a great deal of experience and expertise in order to be able to interpret the produced results. The utilization of smart materials has also been proposed for crack detection. In particular, a sensing skin has been proposed for crack detection and localization in concrete (Kollosche et al. 2011), wood (Laflamme et al. 2013), and steel (Kharroub et al. 2015) specimens.

## **Terrestrial Laser Scanning Technology**

Terrestrial laser scanning, also known as light detection and ranging (LiDAR), enables the direct acquisition of 3D coordinates from the surface of a target object or scene that are visible from the laser scanner's viewpoint (Alba et al. 2011, Vosselman and Maas 2010, Xiong et al. 2013). TLS is based on either time-of-flight (TOF) or phase-based technology to collect the range (x, y, z) and intensity data of objects in a scene. The two technologies differ in calculating the range, while both acquire each range point in the equipment's spherical coordinate frame by mounting a laser on a pan-and-tilt unit that provides the spherical angular coordinates of the point. TOF scanners emit a pulse of laser light to the surface of the target object or scene and calculate the distance to the surface by recording the round trip time of the laser light pulse. Phase-based scanners measure phase shift in a continuously emitted and returned sinusoidal wave. Both types of TLS achieve similar point measurement accuracies. They differ in scanning speed and maximum scanning range. Typically, phase-based TLS achieves faster data acquisition (up to one million points per second), while TOF-based TLS enables collecting data from longer ranges (up to a kilometer).

### *TLS Implementation in the Architecture, Engineering, Construction, and Facilities Management Industry*

Laser scanning technology enables the capturing of comprehensive and very accurate 3D data for an entire construction scene using only a few scans (Cheok et al. 2002). Among other 3D sensing



technologies, laser scanning is the best adapted technology for capturing the 3D status of construction projects and the condition of infrastructure accurately and efficiently. In a study by Greaves and Jenkins (2007), it was shown that the 3D laser scanning hardware, software, and services market has grown exponentially in the last decade, and the architecture, engineering, construction and facilities management (AEC-FM) industry is one of its major customers. This shows that owners, decision makers, and contractors are aware of the potential of using this technology for capturing the 3D as-built status of construction projects and the condition of infrastructure.

Laser scanners can output extremely high resolution models, but at a much larger file size and processing time (Boehler et al. 2003). Despite the remarkable accuracy and benefits, laser scanners' current adoption rate in the AEC-FM industry is still low, mainly because of the data acquisition and processing time and data storage issues. Full laser scanning requires a significant amount of time. Depending on the size of the site, it can take days for large-scale high-resolution shots. Accordingly, the resulting data file sizes are typically very large (e.g., a single high-resolution scan file size could be a couple of gigabytes or much larger). Therefore, data storage and processing are the two biggest factors for the low adoption rates of laser scanners in the AEC-FM industry.

Therefore, there is a need for advanced algorithms that enable automated 3D shape detection from low-resolution point clouds during data collection. This would improve project productivity as well as safety by reducing the amount of time spent on site. Importantly, the practical applications of the developed algorithms to field laser scanners will be straightforward because commercially available laser scanners on the market are generally programmable (Trimble Navigation Limited 2015).

### **Point Cloud Processing using Adaptive Wavelet Neural Networks**

In its raw format, TLS point cloud data contains a significant number of data points that are unstructured and densely and non-uniformly distributed (Meng et al. 2013). Therefore, in the machine learning community, substantial effort has been put into reconstructing 3D shapes from point clouds. Popular reconstruction methods include the utilization of splines (Gálvez and Iglesias 2012) and partial differential equations (PDE) (Wang et al. 2012), the latter of which are seen as an improvement over splines in terms of the number of parameters. Neural networks have also been proposed and demonstrated as superior to PDE-based methods in Barhak and Fisher (2001).

The overarching goal of this research is to detect 3D shapes from point clouds in real-time while scanning on site. However, there exist critical challenges in designing a shape reconstruction algorithm for real-time adaptive scanning:

- The algorithm must adapt sequentially to enable adaptive scanning.
- The representations must be compact to reduce demand on memory. A compact representation can also facilitate queries over a large database, which is particularly useful in extracting prior information in the case of sequential training.

- The number of parameters must remain low to accelerate computational speed. A high number of parameters would result in a substantial lag in the parameterization process.
- The algorithm must be robust with respect to noise in the data, which can be substantial with TLS-based technologies.

Neural networks have been proposed as candidates for providing robust and compact representations. In particular, radial basis function (RBF) neural networks have been applied to the problem of shape reconstruction (Bellocchio et al. 2013). Compared against traditional types of neural networks, they provide a better approximation, better convergence speed, optimality in solution, and excellent localization (Suresh et al. 2008). Furthermore, they can be trained more quickly when modeling nonlinear representations in the function space (Howlett and Jain 2001). Recent work has been published that utilizes sequential RBF networks for reconstructing surfaces from point clouds (Meng et al. 2013). A self-organizing mapping (SOM) architecture has been used to optimize node placement, and the algorithm provided good accuracy with a minimum number of nodes (Kohonen 2001).

The authors of the present report have developed a sequential adaptive RBF neural network for real-time learning of nonlinear dynamics (Laflamme and Connor 2009) and found similar conclusions to those of previous studies, in that the network showed better performance with respect to traditional neural networks. They also designed WNNs for similar applications in Laflamme et al. 2011 and 2012. WNNs are also capable of universal approximation, as shown in Zhang and Benveniste (1992). This particular neural network has also been demonstrated as capable of learning dynamics on the spot without prior knowledge of the underlying dynamics and architecture of the input space.

The study presented in this project report proposes a novel adaptive WNN-based approach to automatically detect concrete cracks from TLS point clouds for bridge structural condition assessment. The adaptive WNN is designed to self-organize, self-adapt, and sequentially learn a compact reconstruction of the 3D point cloud. The approach was tested on a cracked concrete specimen, and it successfully reconstructed 3D laser scan data points as wavelet functions in a more compact format, where the concrete crack was easily identified. This is a significant improvement over previous TLS-based crack detection methods because this approach does not require a priori knowledge about the crack or the 3D shape of the object being scanned. It also enables 3D point cloud data to be processed more quickly and cracks to be detected automatically. Furthermore, because it is designed to self-organize, self-adapt, and sequentially learn a compact reconstruction of the 3D point cloud, it can easily be adapted for real-time scanning in the field, which will be investigated in the future using the adaptive WNN approach presented in this report.

## **CURRENT BRIDGE INSPECTION PRACTICES**

A number of structural engineers and bridge inspectors from the Nebraska Department of Roads (NDOR) and the Iowa DOT were contacted in order to document these agencies' current bridge inspection practices. Semi-structured interviews that were conducted with these authorities helped in pinpointing the needs and requirements for improving current inspection methods. The main idea was to document major problems and issues faced by the authorities in their bridge maintenance and repair operations such as field observations, bridge inspections, and bridge data management. The authorities were asked about the general protocol and methodology followed for bridge inspection practices (see the Appendix). Moreover, the survey was specifically designed to document the visual inspection methodologies carried out by the Iowa DOT and NDOR for the detection of cracks on reinforced concrete bridges as well as the methodologies' advantages and limitations.

### **Nebraska Department of Roads**

The NDOR Bridge Division follows its bridge evaluation manual for bridge inspections. The bridge inspection procedure is initiated by carrying out visual inspection and some nondestructive testing protocols, such as ultrasonic testing methods, to evaluate the condition of bridges. In the case of concrete bridges, NDOR uses a visual inspection method for the detection of cracks and chain dragging and hammers to locate spalled concrete on decks. One National Bridge Inspection Standards (NBIS) inspector/load rating engineer at NDOR who was interviewed as part of this study stated that the visual inspection method is relatively easy and quick. After visually inspecting all the elements of a bridge, the quantities of the areas with cracks and the cracks' severity are measured and documented. However, NDOR has acknowledged that the visual inspection method has its own limitations, in that it is a challenging task to detect small hairline cracks. Also, due to weather conditions some small cracks may close up, which makes it almost impossible to detect them by the naked eye. NDOR carries out bridge inspections every 24 months; however, bridges that meet certain criteria may need to be inspected more frequently.

### **Iowa DOT**

In order to maintain its bridge inventory, the Iowa DOT uses the Structure Inventory and Inspection Management System (SIIMS) (Iowa DOT 2014). For the purpose of detecting cracks on various elements of a bridge, the Iowa DOT uses field inspection, including visual inspection and other nondestructive means of evaluation such as a dye penetrant test, magnetic particle testing methods, ultrasonic testing methods, etc. When implementing the visual inspection method, critical areas are cleaned prior to inspection and additional lighting sources and magnification techniques are employed if required. The inspectors take photographs of the cracked elements, and the exact crack conditions are sketched and documented. The process of visual inspection for crack detection is typically carried out in a 24-month period (Iowa DOT 2014).

## RESEARCH METHODOLOGY

### Adaptive Wavelet Network

An adaptive WNN was designed to sequentially learn a compact reconstruction of a 3D point cloud. The architecture of the WNN is based on a single-layer neural network, as illustrated in Figure 2, and consists of  $h$  Mexican hat wavelets centered at  $\mu_i$ , with a bandwidth of  $\sigma_i$ , where each function (or node)  $\phi_i$  can be written as follows:

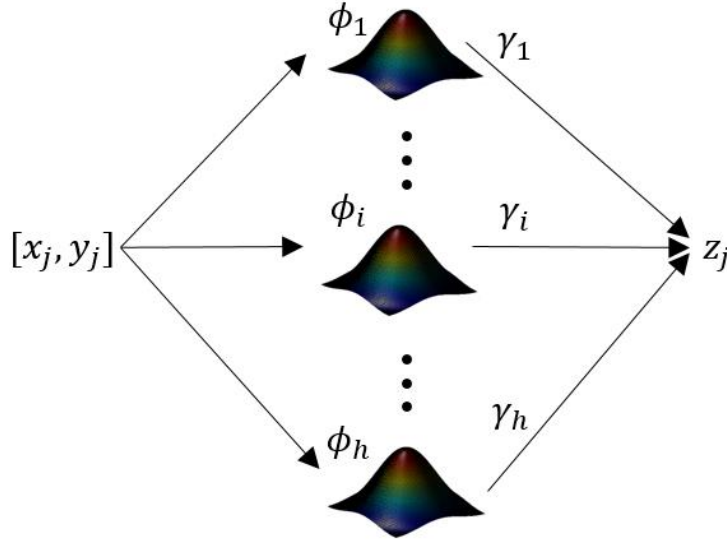
$$\phi_i(\zeta) = \left(1 - \frac{\|\zeta - \mu\|^2}{\sigma^2}\right) e^{-\frac{\|\zeta - \mu\|^2}{\sigma^2}} \quad \text{for } i = 1, 2, \dots, h \quad (1)$$

The wavelet network maps the  $z_j$  coordinate of point  $\zeta_j = [x_j, y_j]$  using the following function:

$$\tilde{z}_j = \sum_{i=1}^h \gamma_i \phi_i(x_j, y_j) \quad (2)$$

where  $\gamma_i$  represents the function weight and the tilde denotes an estimation.

$$\phi_i(\zeta) = \left(1 - \frac{\|\zeta - \mu\|^2}{\sigma^2}\right) e^{-\frac{\|\zeta - \mu\|^2}{\sigma^2}} \quad \text{for } i = 1, 2, \dots, h$$



**Figure 2. Single-layer architecture of the wavelet network**

The network is self-organizing, self-adaptive, and sequential. The self-organizing feature consists of the capability to add functions at sparse locations. This is done following Kohonen's Self-Organizing Mapping Theory (Kohonen 2001). The self-adaptive feature consists of adapting the network parameters  $\sigma$  and  $\gamma$  to learn the compact representation. Lastly, the sequential

feature refers to the capability of the network to learn a representation while scanning is occurring, in a sequential way, in opposition to a batch process. This sequential capability can be used to interact with the 3D scanner in real-time.

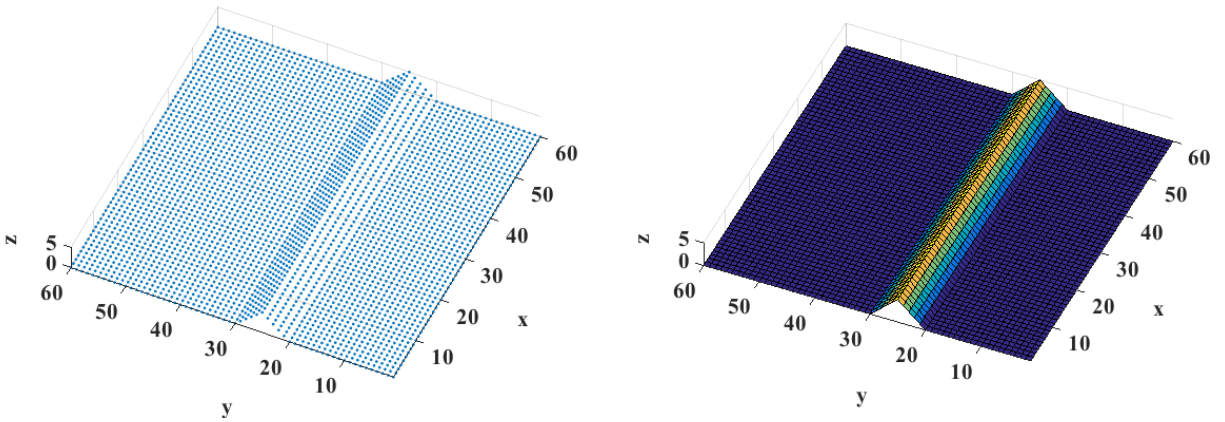
The wavelet network algorithm is described as follows. First, a new point  $\zeta_j$  is queried from the scanner, along with its associated  $z_j$ . The shortest Euclidean distance is computed between the location of the new point  $\zeta_j$  and the center of the existing functions  $\mu_i$  for  $i = 1, 2, \dots, h$ . If the shortest distance is greater than a user-defined threshold  $\lambda$ , a new function is added at  $\mu_{h+1} = \zeta_j$ , and the number of functions increases by 1. Note that this threshold decreases with decreasing bandwidth  $\sigma_i$ , which allows the creation of denser regions where the network resolution is higher. The weight of the new function is taken as  $\gamma_{h+1} = z_j$ . Second, if no new function is added, the estimate  $\tilde{z}_j$  is compared against the value  $z_j$ , and the network error  $e = \tilde{z}_j - z_j$  is computed. Third, the network parameters  $\sigma_i$  and  $\gamma_i$  are adapted using the backpropagation method (Laflamme et al. 2012):

$$\dot{\xi} = -\Gamma_{\xi} \left( \frac{\delta z}{\delta \xi} \right) e \quad (3)$$

where  $\xi = [\sigma, \gamma]$  and  $\Gamma_{\xi}$  are positive constants representing the learning rate of the network.

### Assessment of Adaptive WNN Algorithm

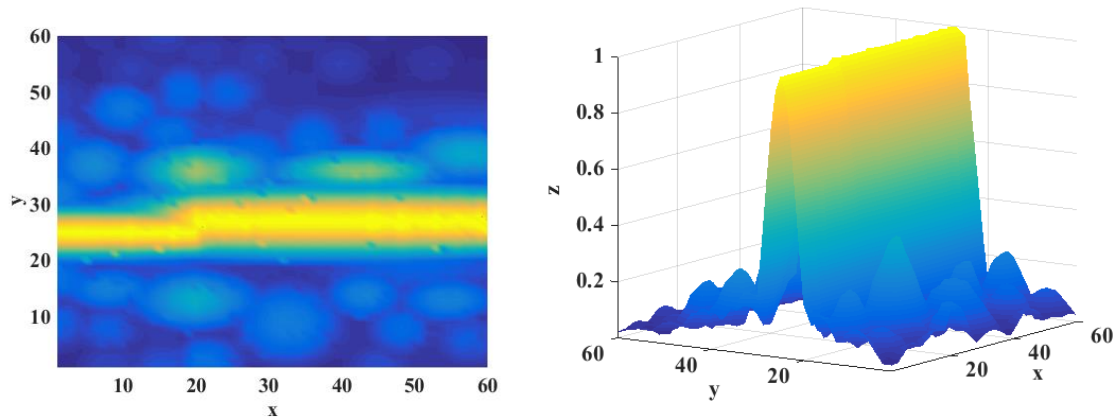
First, we generated an artificial data set to test the proposed adaptive WNN algorithm. As can be seen in Figure 3, a crack appears as an anomaly in the data.



**Figure 3. Artificial test data set**

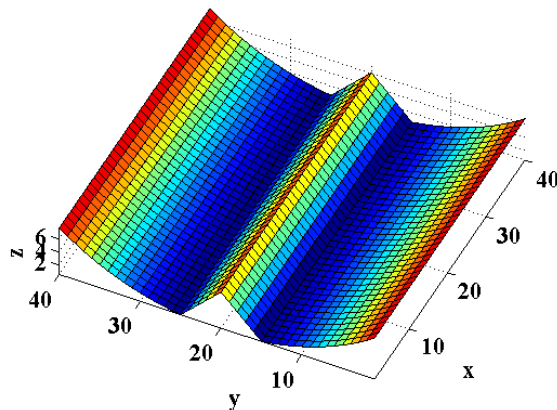
This artificial data set was trained using the adaptive WNN with data points represented with nodes, and the results show that the weights (heights) of the nodes in the area where the crack is located are larger than those of the nodes located in the flat area.

In Figure 4, the results clearly show that the crack is located between 20 mm and 30 mm on the y-axis.



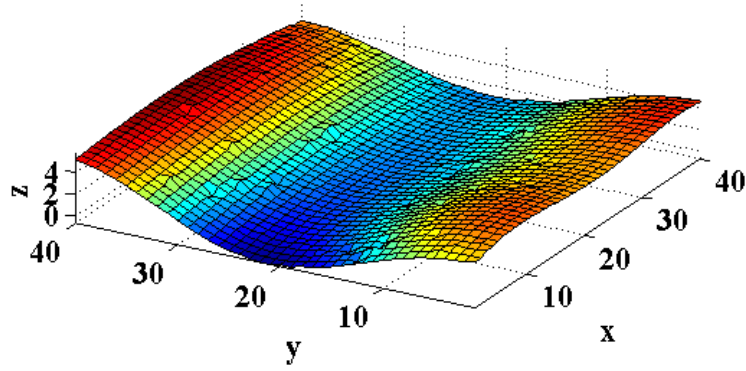
**Figure 4. Normalized results: top view (left) and side view (right) of crack location**

After the first test, we applied the method to a more complex artificial data set containing a curved surface as opposed to a flat surface (Figure 5).



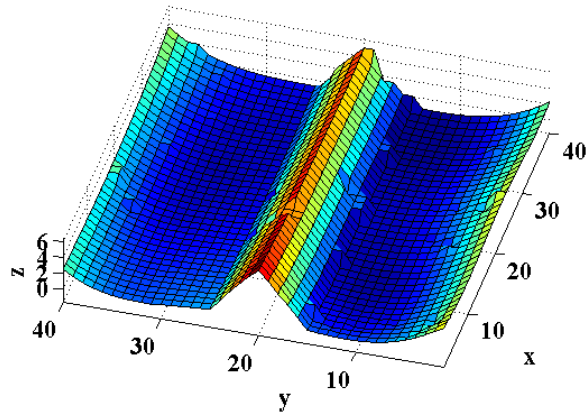
**Figure 5. Second test data set**

First, large initial bandwidth values were used to do a low-resolution fit (Figure 6), which contained most of the half-circle feature and little information about the crack.



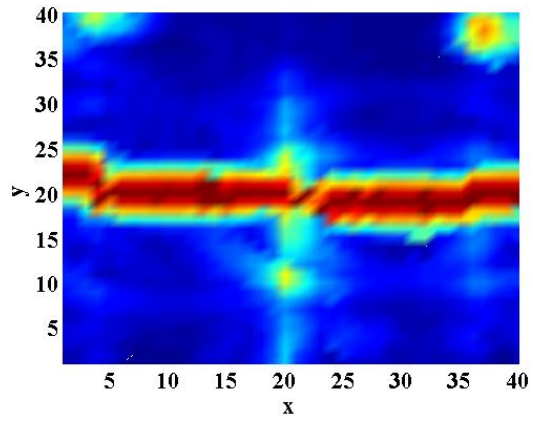
**Figure 6. Low-resolution fit**

Then we subtracted the original data from the low-resolution fit to get the “difference data” (Figure 7).



**Figure 7. Difference data**

This way, the half-circle feature contained in the “difference data” could be ignored. We then applied a high-resolution fit to the “difference data” and were able to identify the crack. Figure 8 shows clearly that the crack is located between 15 and 25 on the y-axis.



**Figure 8. Crack location**



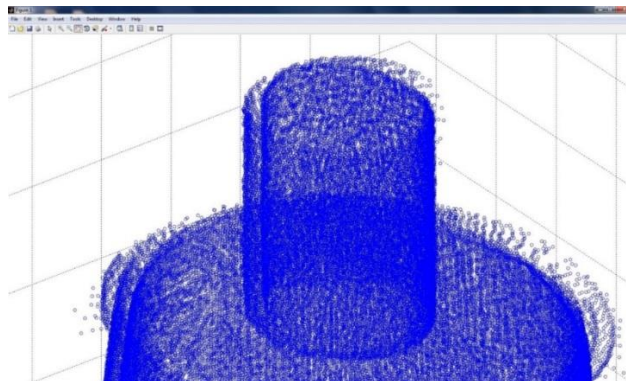
## DATA COLLECTION

A test bed consisting of concrete cylinders with different dimensions was set up in the Structural Engineering Research Laboratory in the Department of Civil, Construction, and Environmental Engineering at Iowa State University. Cracked concrete cylinders of various sizes ranging from 100 mm to 200 mm in diameter and 100 mm to 300 mm in height, with different crack widths, orientations, and depths, were obtained from the laboratory so that the crack detection algorithms could be tested to detect cracks of different sizes. The laser scan point cloud data was collected using a phase-based laser scanner, the Trimble TX5 (Figure 9).



**Figure 9. Laser scanning of a concrete block**

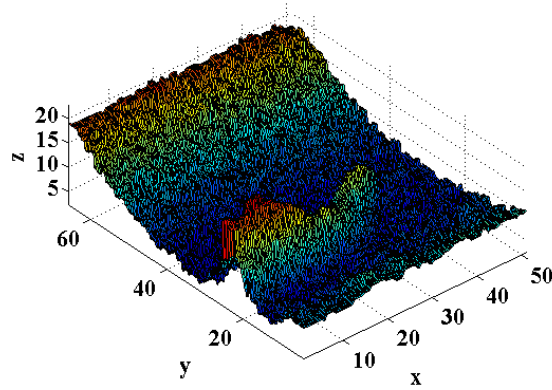
The captured point cloud data was processed using MATLAB, a proprietary programming language (Figure 10).



**Figure 10. 3D point cloud of a concrete block (plotted in MATLAB)**

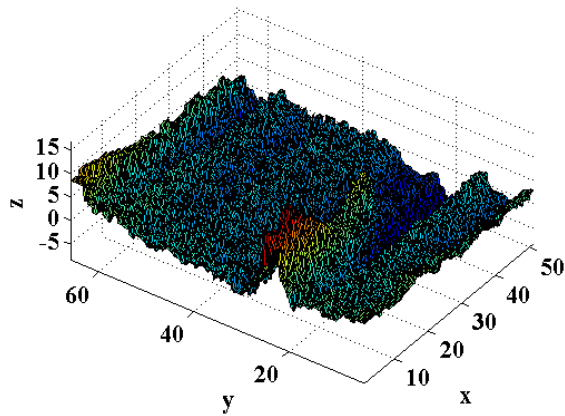
## PRELIMINARY RESULTS

After the successful implementation of the adaptive WNN algorithm on the artificial data, the algorithm was applied to the real-life data collected from the Structural Engineering Research Laboratory. Figure 11 shows the original point cloud data plotted in MATLAB.



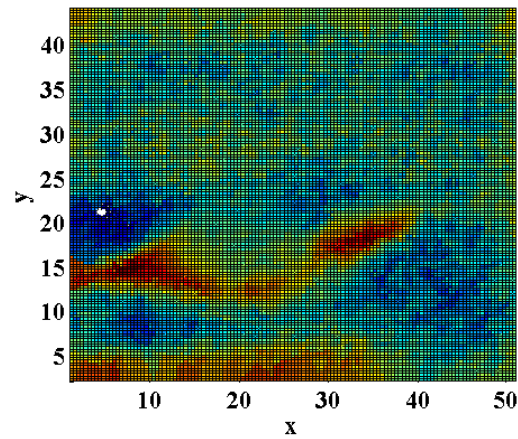
**Figure 11. Original data plotted in MATLAB**

Figure 12 shows the difference data plotted in MATLAB.

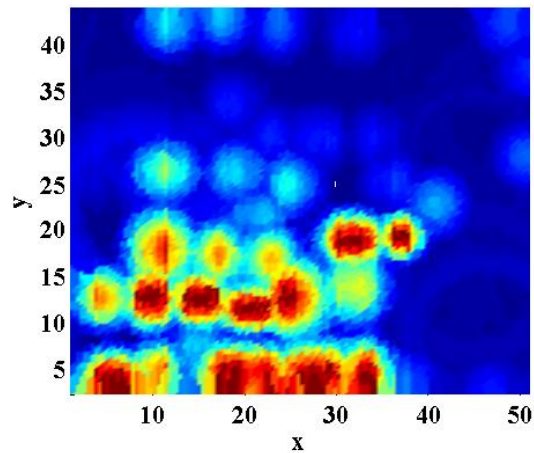


**Figure 12. Difference data plotted in MATLAB**

Figure 13 and Figure 14 show the crack location clearly (red-colored area between 10 and 15 on the y-axis).



**Figure 13. Top view of difference data**

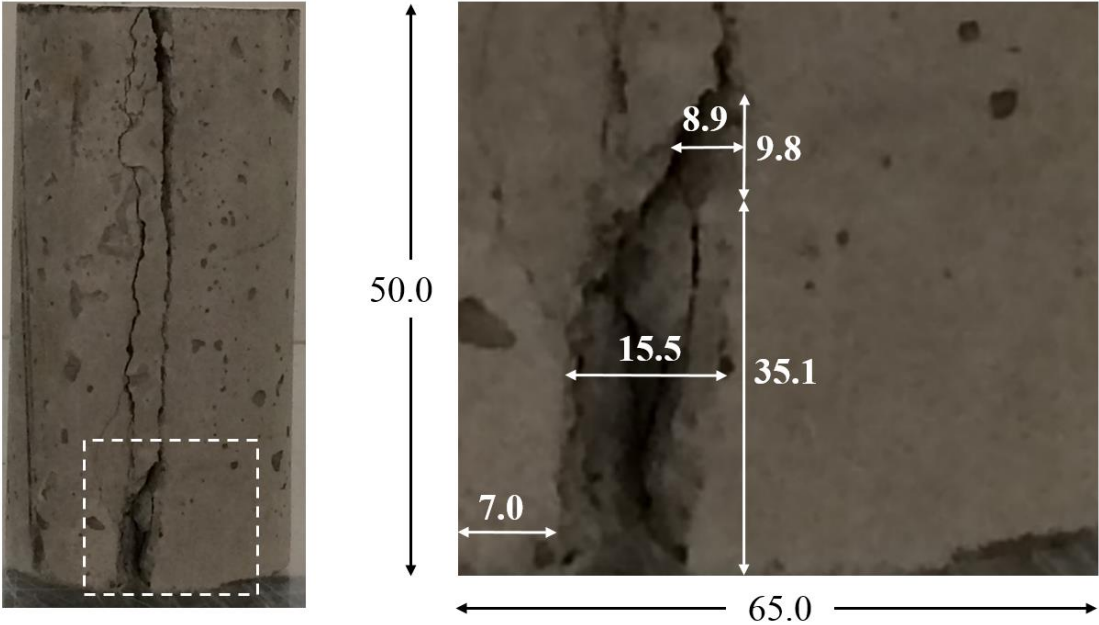


**Figure 14. Location of crack**

However, one thing that needs to be paid attention to is the red-colored area at the bottom of the images. This occurred due to the fact that the cylinder size was small and the crack was very close to the bottom edge. Therefore, the parameters of the WNN nodes located at the bottom were affected by the nodes located in the cracked area.

**EXPERIMENTAL RESULTS**

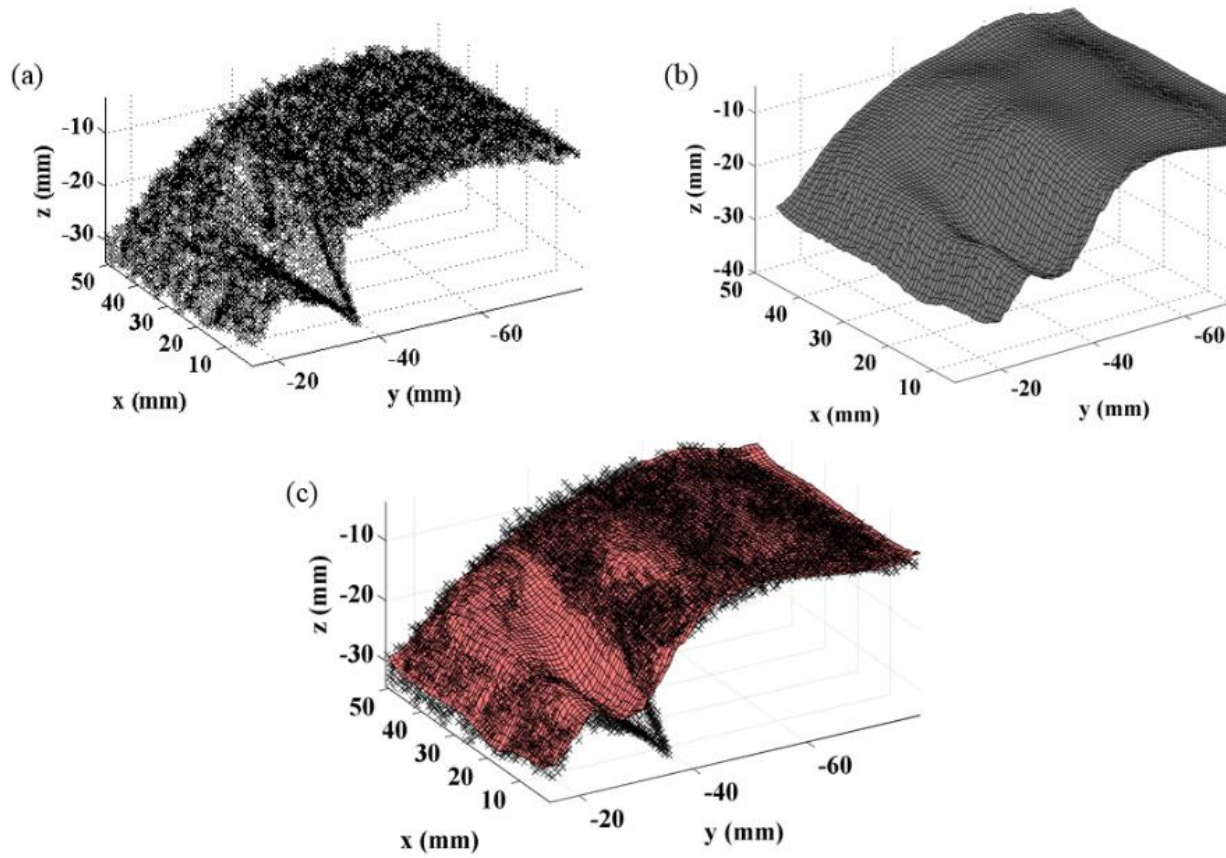
The adaptive wavelet network was validated on a cracked concrete specimen. The specimen was scanned using a Trimble TX5 phase-based TLS on a region limited to 50 by 65 mm<sup>2</sup> to focus the study on the algorithm itself. A total of 8,170 points were generated. The specimen is shown in Figure 15, along with a zoom on the limited region (right).



**Figure 15. Specimen (scanned region shown by the dashed rectangle, left) and zoom on the scanned region (distances in mm, right)**

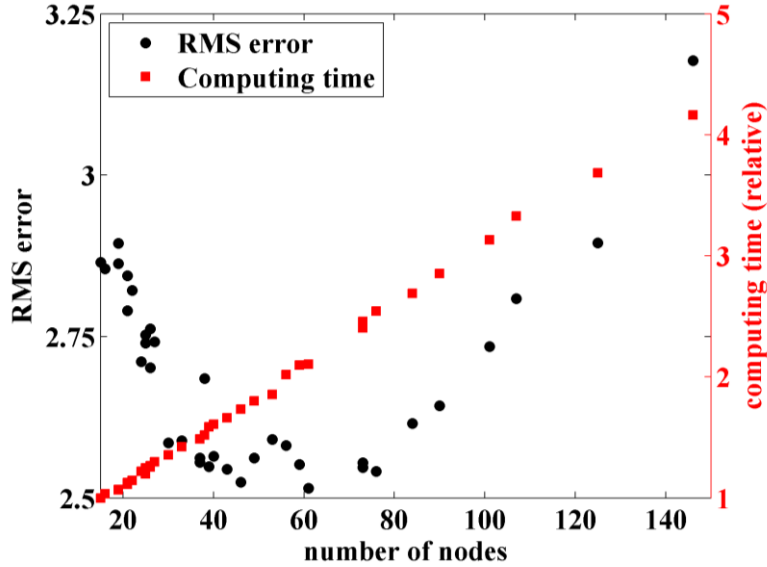
Figure 15 (right) shows the crack that runs through the region, with a wider region along the first 35.1 mm from the bottom and a smaller damage geometry along 9.8 mm and after.

Figure 16 shows a typical fitting result obtained using 59 nodes.



**Figure 16. (a) Point cloud, (b) compact representation, and (c) overlap of point cloud and representation**

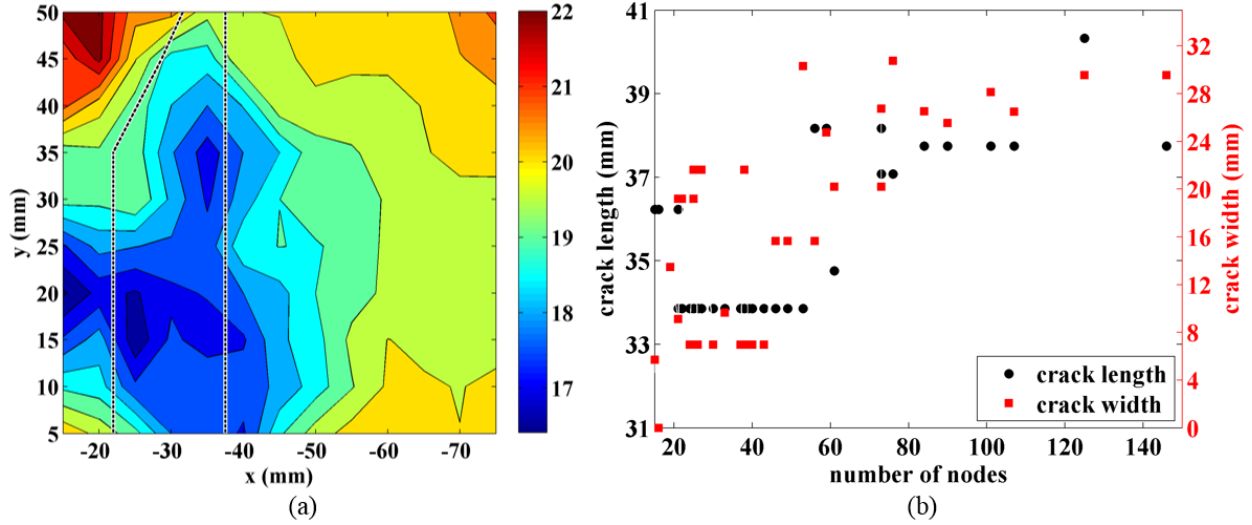
The compact representation provides a good fit of the 3D point cloud and includes the damage feature. A study was conducted on the accuracy of the representation as a function of the number of nodes in the network, in which the parameter  $\lambda$  was changed while keeping all other network parameters constant. The accuracy was measured in terms of the root mean square (RMS) error. Figure 17 is a plot of the RMS error as a function of the number of nodes.



**Figure 17. RMS error and relative computing time versus wavelet network size**

Figure 17 also shows the relative computing time versus the network size. In this case, there is a region in which the algorithm provides an optimal representation in term of RMS error. The decrease in performance for a higher number of nodes can be attributed to the network parameters that become mistuned. In particular, when more nodes are allowed in the network and the initial bandwidth is large, one would expect a relatively higher training period to obtain an acceptable level of accuracy. The relative computing time changes linearly with the number of nodes in the network.

While the wavelet network provides an accurate representation of the 3D point cloud, it should also be capable of extracting key features, such as damage. With this particular example, an attempt was made to automatically localize the damage and determine its severity. The strategy consisted of identifying regions of wavelets (or nodes) of lower bandwidths, which would indicate a region of higher resolution and thus the location of a more complex feature (a crack, in this case). Figure 18(a) is a wavelet resolution map, which is obtained by computing the average wavelet bandwidth within a region of the representation.



**Figure 18. (a) Wavelet resolution map showing the average wavelet bandwidths for a representation using 59 nodes (the approximate crack region is shown within the black-dashed region) and (b) identified crack length and width based on wavelet resolutions**

Dark blue areas in Figure 18(a) indicate a high-resolution region, while dark red areas represent low-resolution regions. The damage is approximately localized using this strategy. Next, the crack length and width were estimated by evaluating the maximum distances along the x- and y-axes within a group of wavelets of low bandwidth.

Figure 18(b) is a plot of the computed crack length and width as a function of the number of nodes. The approximate crack length is more accurately determined for networks created with a large number of nodes, but it yields an acceptable approximation. The estimated crack width increases with the increasing number of nodes. This is explained by the presence of a high-resolution region around coordinate [-20, 20], shown in Figure 18(a), which is perceived as a crack. A representation created with a large number of functions may over-fit the 3D point cloud.

## CONCLUSIONS

A strategy to sequentially construct a compact representation of a 3D point cloud was presented. The representation is wavelet network capable of self-organization, self-adaptation, and sequential learning. It can be utilized to transform thousands of 3D point cloud data obtained from a TLS or LiDAR into a small set of functions.

The proposed wavelet network was demonstrated on a cracked cylindrical specimen. It was shown that the algorithm was capable of replacing a set of 8,170 3D coordinates into a set of 59 functions while preserving the key features of the scan data, which included a crack. By looking at local regions of high-resolution wavelets, it is possible to localize these features and estimate their geometry. While the promise of automatic damage detection has been demonstrated, the development of more complex algorithms in future work could lead to a more accurate numerical localization and estimation of damage.



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## **APPENDIX: SURVEY QUESTIONNAIRE**

### **Questionnaire**

1. What are the current bridge inspection practices followed and what parameters of a bridge are taken under inspection using these methods?
2. What method/s is/are used for detecting cracks on bridges?
3. What are the advantages and challenges for methods used for bridge inspection in terms of accuracy, time, cost and efficiency?
4. How the method of visual inspection of bridges is carried out specifically for crack detection on concrete surfaces? Explain briefly.
5. What are the advantages and limitations for visual inspection method in terms of accuracy, time, cost and efficiency?
6. How frequently bridge inspection practices are carried out in a year's time for a given bridge?