Adaptive Wavelet Neural Network for Terrestrial Laser Scanner-Based Crack Detection

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Abstract

Objective, accurate, and fast assessment of civil infrastructure conditions is critical to timely assess safety risks. Current practices rely on visual observations and manual interpretation of reports and sketches prepared by inspectors in the field, which are labor intensive, subject to personal judgment and experience, and prone to error. Terrestrial laser scanners (TLS) are promising for automatically identifying structural condition indicators, as they are capable of providing coverage for large areas with accuracy at long ranges. Major challenges in using this technology are in storing significant amount of data and extracting appropriate features enabling condition assessment. This paper proposes a novel adaptive wavelet neural network (WNN)-based approach to compress data into a combination of low- and high-resolution surfaces, and automatically detect concrete cracks and other forms of damage. The adaptive WNN is designed to sequentially self-organize and self-adapt in order to construct an optimized representation. The architecture of the WNN is based on a single-layer neural network consisting of Mexican hat wavelet functions. The strategy is to first construct a low-resolution representation of the point cloud, then detect and localize anomalies, and finally construct a high-resolution representation around these anomalies to enhance their characterization. The approach was verified on four cracked concrete specimens. The experimental results show that the proposed approach was capable of fitting the point cloud, and of detecting and fitting the crack. The results demonstrated data compression of 99.4\%, 72.2\%, 92.4\% and 78.9\% for the four specimens when using low resolution fit for crack detection. For specimens 1, 2 and 3, 97.1\%, 42.5\% and 63.9\% compression of data were obtained for crack localization, which is a significant improvement over previous TLS based crack detection and measurement approaches. Using the proposed method for crack detection would enable automatic and remote assessment of structural conditions. This would, in turn, result in reducing costs associated with infrastructure management, and improving the overall quality of our infrastructure by enhancing maintenance operations.

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1. Introduction

Every four years, American Society of Civil Engineers (ASCE) releases a comprehensive assessment of the U.S. infrastructure. The most recent report card that was published in 2017 gave an overall grade of D+ (poor) for the nation’s infrastructure, C+ (mediocre) for bridges (ASCE 2017) (Petroski 2016). Catastrophic events are rare, but the federal National Bridge Inventory classified 56,007 bridges out of 614,387 as structurally deficient. In May 2013, the I-5 Skagit bridge, which was a through truss bridge built in 1955, near Seattle, WA collapsed into the river below when an oversized truck scraped several overhead girders of the bridge. The sudden collapse of I-35W Mississippi River bridge during evening rush hour in 2007, killed 13 people and injured 145. In 1990, federal government had rated this bridge as “structurally deficient” due to the significant corrosion in its bearings. In 2007, approximately 75,000 other US bridges had this rating. These numbers emphasize the urgent need for more frequent and comprehensive bridge inspections to prevent further catastrophic events. However, the budget available for infrastructure is limited. Therefore, there is a need for finding cheaper and faster ways to maintain and operate our infrastructure.

National Bridge Inspection Standards (NBIS) require routine inspections to assess the condition of bridges on the National Highway System. These inspections, conducted using printed checklists, are typically performed by trained inspectors using visual inspection techniques that are heavily subjective (Phares, et al. 2001) (Phares, et al. 2004). 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 transcribe it to the bridge evaluation database after arriving back at his/her office. This is a complex and time-consuming set of responsibilities that are prone to error.


TLS technology, an advanced three-dimensional (3D) imaging technology is employed to gather the data used in this study. TLS rapidly measures the 3D coordinates of densely scanned points within a scene. The data gathered by a TLS is provided in the form of 3D point clouds with color and intensity data associated with each point within the cloud. Point cloud data can be analyzed using various computer vision algorithms and methods to detect structural conditions (Koch, et al. 2015), e.g. concrete cracks (Abdel-Qader, et al. 2006) (Yamaguchi, et al. 2008) (Yamaguchi and Hashimoto 2010) (Prasanna, et al. 2012) (Abdel-Qader, et al. 2003) (Koch, et al. 2014) and spalling (Adhikari, et al. 2013) (German, et al. 2012).
However, there is limited research conducted on employing TLS to detect and classify cracks automatically for infrastructure condition assessment. Previous research in this area mainly focused on manual detection and measurements of cracks, displacements or shape deflections from TLS point clouds (Chen 2012) (Chen, et al. 2014) (Olsen, et al. 2013). In its raw format, TLS point cloud data contains significant number of data points that is unstructured, densely and non-uniformly distributed (Meng, et al. 2013). To overcome the difficulties of manual data processing, in machine learning community, substantial effort has been put in automatically reconstructing 3D shapes from point clouds. The most popular reconstruction methods include the utilization of Splines (Galvez and Iglesias 2012) and partial differential equations (PDE) (Wang, et al. 2012), which was seen as an improvement over Splines in terms of numbers of parameters. Neural networks have also been proposed and demonstrated as superior to PDE-based methods in (Barhak and Fischer 2001) as they provide robust and compact representations of the data. In particular, Radial Basis Functions (RBF) neural networks have been applied to the problem of shape reconstruction (Bellocchio, et al. 2013). Compared to traditional types of neural networks, they provide a better approximation, convergence speed, optimality in solution and excellent localization (Suresh, et al. 2008). Furthermore, they can be trained faster when modeling nonlinear representations in the function space (Howlett and Jain 2001). Recent work has been published in utilizing sequential RBF networks for reconstructing surfaces from point clouds (Meng, et al. 2013). A self-organizing mapping (SOM) (Kohonen 1990) architecture was used to optimize node placement, and the algorithm provided good accuracy with minimum number of nodes. Laflamme and Connor have developed a sequential adaptive RBF neural network for real-time learning of nonlinear dynamics and returned similar conclusions where the network showed better performance with respect to traditional neural networks (Laflamme and Connor 2009). They also designed wavelet neural networks (WNN) for similar applications (Laflamme, et al. 2012). WNN are also capable of universal approximation (Zhang and Benveniste 1992) (Doulamis, et al. 2000) (Haykin 2006). 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.

This paper proposes a novel adaptive wavelet neural network (WNN)-based approach to construct compact 3D representations and automatically detect features, here concrete cracks, from TLS point clouds for infrastructure condition assessment. The adaptive WNN is designed to self-organize, self-adapt, and sequentially learn a compact reconstruction of the 3D point cloud. The strategy is to first construct a low-resolution representation of the point cloud, then detect and localize anomalies, and finally construct a high-resolution representation around these anomalies to enhance their characterization. In future studies, such strategy could be used to guide the TLS, in real-time, for constructing accurate representation containing features of interest.

The proposed approach was verified on four cylindrical cracked concrete specimens. The method successfully reconstructed the 3D laser scan data points as wavelet functions in a more compact format for all four specimens. Features were extracted from the compact representation to detect the crack location and quantify the accuracy of the reconstructed cracks in terms of Root Mean Square (RMS) error, where the error is defined as the difference between
the wavelet representation and the TLS data. This is a significant improvement over previous TLS based crack detection methods as it does not require prior knowledge about the crack or the 3D shape of the object being scanned. It also enables to process 3D point cloud data faster, which is very important, especially when working with large data sets.

2. Background

In this section, comprehensive background information is provided on the state of the art in crack detection on concrete structures, TLS technology as well as its implementation in the AEC-FM industry and details of the WNN algorithm used in this study.

2.1 Defect Detection in Concrete Structures

Over the past years, several research efforts have been directed towards automatically detecting defects in concrete structures. Majority of the methods that are proposed thus far rely on collecting images of the concrete structures for inspection purposes.

High resolution cameras mounted on Unmanned Aerial Vehicle (UAV) systems have been proposed to collect images for detecting cracks. A critical advantage of UAVs is that they are not bounded by terrain motion constraints and vision range limitations (Metni and Hamel 2007). A Micro Air Vehicle (MAV) mounted with a high resolution digital camera was used to acquire images for building inspection (Eschmann, et al. 2012). In this study, edge detection method was used to detect structural cracks. The edge detection method is based on applying a Gaussian Blur, the result of blurring an image by a Gaussian function, to the original image and subtracting the blurred image from the original image. Similarly, Sankarasrinivasan et al. (2015) applied hue, saturation, and value (HSV) thresholding technique to detect structural cracks in images collected using a Multi Rotor UAV (MUAV) system.

Machine learning and image processing methods have been used in (Moussa and Hussain 2011) to automatically detect, classify and estimate crack parameters. In this study, the authors used Support Vector Machines (SVM) to classify the cracks into transverse, longitudinal, block, and alligator cracking patterns. The crack length and width parameters were calculated using random sample consensus (RANSAC) algorithm. The approach described in (Valença, et al. 2013) exploits the synergy between photogrammetry and image processing techniques to detect cracks in concrete specimens. It uses the strain field obtained from finite element analysis to map critical crack regions, thus constraining the image processing to critical areas of interest. Photogrammetry technique was used to measure crack thickness in (Jahanshahi and Masri 2013). A comprehensive review on computer vision based defect detection and condition assessment of concrete structures can be found in (Koch, et al. 2015).

The development and application of intelligent robotic systems for defect detection in civil infrastructure is advancing rapidly. Several robotic tunnel inspection systems have been developed with the objective of improving safety in hazardous data collection environments and efficiently carrying out tunnel inspection processes (Montero, et al. 2015). As a part of the
ROBO-SPECT project, a tunnel assessment approach was developed and tested on the Metsovo Motorway tunnel (Makantasis, et al. 2015) (Stentoumis et al. 2016). The approach used a convolutional neural network (CNN) to extract features describing defects from RGB images and a Multi-Layer Perceptron was used to categorize image pixels into defect and non-defect categories. A robotic platform, developed under the ROBO-SPECT project, was used to detect cracks in the Egnatia Motorway tunnel (Loupos, et al. 2017) (Protopapadakis, et al. 2016). This platform uses RGB cameras, a laser scanner and an ultrasonic sensor to detect and collect data from regions containing cracks. The crack detection algorithm is based on a CNN.

2.2 Terrestrial Laser Scanning (TLS) Technology

TLS is an advanced 3D imaging technology that is used to rapidly measure the 3D coordinates of densely scanned points within a scene. 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. TLS technology enables 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). There are two types of TLS based on the technology they use to acquire range (x, y, z) and intensity data of objects in a scene; namely time-of-flight (TOF) TLS and phase-based TLS. 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 achieve faster data acquisition (up to one million points per second) and has an accuracy of 0.4 mm at a range of 11 m. TOF-based TLS enables collecting data from longer ranges (up to a kilometre) and has an accuracy of 6 mm at a range of 100 m.

2.2.1 TLS implementation in the AEC-FM Industry

TLS technology enables capturing 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, TLS is the best adapted technology for capturing the 3D status of construction projects and condition of infrastructure accurately and efficiently. In a study by (Greaves and Jenkins 2007), it is 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 condition of infrastructure. Despite the remarkable accuracy and benefits, current adoption rate of laser scanners in the AEC-FM industry is relatively low, mainly because of the data acquisition and processing time and data storage issues. Laser scanners are capable of producing high resolution models of construction sites, but at the cost of large file sizes and increased data processing time (Boehler and Marbs
Thus, there is a need for advanced algorithms to represent the large data files in a compact form while enabling automated 3D shape detection from the compact representation. This would improve project productivity as well as safety by reducing the amount of time spent on-site.


2.3. Wavelet Neural Network (WNN)

The representation of the 3D object is constructed using a single-layer Wavelet Neural Network (WNN). This particular architecture was selected due to its known universal approximation capability and demonstrated fast convergence, as discussed in the introduction. The network comprises $h$ nodes or activation functions $\phi$ consisting of Mexican Hat wavelets

$$\phi_i(\boldsymbol{\zeta}) = e^{-\frac{\|k - \mu_k^2}{\sigma^2}} \quad \text{for} \quad i = 1, 2, ..., h$$

(1)

centered at $\mu_i$, with a bandwidth $\sigma_i$, and where $\boldsymbol{\zeta}$ is the input vector. The wavelet network maps the $z$ coordinate of point $\boldsymbol{\zeta}_j = [x_j, y_j]$ using the function

$$\hat{z}_j = \sum_{i=1}^{h} y_i \phi_i(\boldsymbol{\zeta})$$

(2)

where $y_i$ are weights, and the hat denotes an estimation. The normalizing factor of the wavelet in eqn. (1) is intentionally omitted as the weights, $y_i$ in eqn. (2) account for them. A representation of the WNN with 2D Mexican hat wavelets is illustrated in Figure 1.

The network is designed to be 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 (SOM) Theory (Kohonen 1982) (Kohonen 1990) (Kohonen, et al. 1996). The self-adaptive feature consists of adapting the network...
parameters $\mathbf{\sigma}$ and $\mathbf{\gamma}$ to learn the compact representation. The sequential feature refers to the capability of the network to learn in a sequential manner, as opposed to batch processing. We built this sequential feature for real-time applications in combination with a controllable TLS. Such real-time interaction with a TLS is left to future work.

![Figure 1: Representation of the wavelet neural network architecture.](image)

### 2.2.1 Self-Organization

SOM theory is used to optimize the node placement. A coordinate $\zeta_j$ is queried from the scanner, along with its associated $z_j$. The shortest Euclidean distance is computed between $\zeta_j$ and the center of the existing nodes $\mu_i$ for $i = 1, 2, ..., h$. If the shortest distance is greater than a user-defined threshold $\lambda$, a new node is added at $\mu_{h+1} = \mu_j = [x_j, y_j]$ with a predefined bandwidth $\sigma_0$. The selection of $\lambda$ defines the resolution of the network, where a small value for $\lambda$ will yield a larger number of nodes at a higher resolution by larger overlaps of wavelets. Other factors which govern the resolution of the network include the initial bandwidth, $\sigma_0$ and the selected learning rates used to adapt the wavelet parameters. The initial weight of the new function is set such that $y_1 = z_j$. Remark that the network is initialized with $h = 0$, and the very first scan will give rise to the first node of the network.

### 2.2.2 Sequential Self-Adaptability

At each scan step $k$, the WNN error $\tilde{z}_j = \hat{z}_j - z_j$ is computed and parameters $\sigma^2_i$ and $\gamma_i$ are adapted using the back-propagation method (Laflamme, et al. 2012):

$$\dot{\xi} = -\Gamma_\xi \left( \frac{\partial \phi}{\partial \xi} \right) \tilde{z}$$

where $\xi = [\sigma^2, \gamma]$, and $\Gamma_\xi$ are positive constants representing the learning rates. In discrete notation, the back-propagation rule for $\sigma^2$ and $\gamma$ can be written as below:

$$\sigma^2_{i,k+1} = \sigma^2_{i,k} - \Gamma_{\sigma^2} Y_{i,k} \left( \frac{||\zeta - \mu_i||^2}{\sigma^2_{i,k}} - \frac{-||\zeta - \mu_i||^2}{\sigma^4_{i,k}} \right) \tilde{z}_j$$

$$\gamma_{i,k+1} = \gamma_{i,k} - \Gamma_{\gamma} Y_{i,k}$$

where $Y_{i,k}$ is the learning rate for $\gamma_i$.
\[ y_{i,k+1} = y_{i,k} - \gamma \left( e^{\sigma_{\phi,k+1}^2} \right) \tilde{z}_j \] (5)

for \( i = 1, 2, ..., h \), where \( h \) is the number of nodes at step \( k \) and \( \sigma_0^2 \) and \( \gamma_0 \) are initial values selected by the user. The simulation ends for a user-defined value of \( k \), which could correspond, for example, to the number of points generated by the TLS or more if additional iterations within the point cloud are desired.

2.2.3 Reconstruction Strategy

The resolution of the representation of the 3D object impacts memory usage and computational time. A higher resolution representation will require a larger number of wavelets (more memory) and consequently more CPU power for larger vector and matrix operations. For practical real-time usage of a controllable TLS, we propose using a low-resolution fit of the 3D point cloud data for creating a quick and compact representation of an object or structure, run analysis on the low-resolution fit to determine damage areas, then re-run algorithm only on problem areas for a detailed high-resolution examination. The algorithm automatically detects the region of crack based on the low-resolution fit. The 3D point cloud data of the region of crack is used to create a high-resolution fit. A block diagram illustrating our reconstruction strategy is showed in Figure 2. When a damage is detected, two sets of data are recorded: the low-resolution data and the high-resolution data. Such strategy results in shorter computational time and smaller data sets to be preserved.

![Figure 2: Block diagram of reconstruction strategy.](image)

3. Experimental Validation

The developed adaptive WNN algorithm-based approach was validated on four cracked concrete specimens. Specimen 1 was scanned using a Trimble TX5 phase-based TLS, while specimens 2, 3 and 4 were scanned using a NextEngine 3D scanner, based on MultiStripe Laser Triangulation (MLT) technology. Specimens 1, 2, 3 and 4 were scanned on rectangular regions limited to 50 by 65 mm², 25 by 40 mm², 90 by 20 mm² and 60 by 30 mm², respectively, to focus the study on the algorithm itself. The specimens are shown in Figure 3(a), 4(a), 5(a) and 6(a), along with a zoom on the limited region (Figure 3(b), Figure 4(b), Figure 5(b) and Figure 6(b)). Figure 3(a) shows the crack that runs through the specimen with a larger damage area (along the first 35.1 mm from the bottom), and a smaller damage geometry along 9.8 mm and after. Figure 4(b) shows specimen 2 with cracks on the left (wide) and the right (narrow), each measuring 25 mm in length from the bottom. Figure 5(b) shows specimen 3 with a long and...
narrow crack that runs throughout the length of the specimen (90 mm in length). A shallow hairline crack of 60 mm in length was observed in specimen 4, as shown in Figure 6(b).

Figure 3: (a) Specimen 1 (scanned region shown by the dashed rectangle); and (b) zoom on the scanned region (dimensions in mm).

Figure 4 (a) Specimen 2 (scanned region shown by the dashed rectangle); and (b) zoom on the scanned region showing two cracks (dimensions in mm).

Figure 5 (a) Specimen 3 (scanned region shown by the dashed rectangle); and (b) zoom on the scanned region showing a long and narrow crack (dimensions in mm).
3.1 Low-resolution fit

A total of 7954 data points was generated for specimen 1, each defined in terms of $x$, $y$, and $z$. The 7954 data points obtained from the 3D scanner have been fitted with a low-resolution surface using 27 nodes. Figure 7(a) shows the fitting result of a crack and curvature for specimen 1. The compact representation provides a good fit of the 3D point cloud and includes an observable damage feature. In this case, 7954 data points have been compacted in 27 nodes that yielded a continuous surface, resulting in a 99.4% compression of data. The data compression rate taken as the change in size of the data set (e.g., size of original data set minus size of new data set) relative to the size of the original data set, where the size of the original data set is the number of laser coordinates multiplied by three (i.e., one data per axis) and the size of the new data set is the number of nodes in the network multiplied by five (i.e., one node has a value assigned over $\sigma_x$, $\sigma_y$, $\mu_x$, $\mu_y$, and $\gamma$). For specimen 2, a low-resolution fit was obtained using 199 nodes and 72.2% compression of data for crack localization. The original number of data points in this case was 1192. Similarly, 204 and 342 nodes were used to achieve a low-resolution representation of the cracks in specimens 3 and 4, respectively. The number of points originally present were 4461 and 2706, respectively. This resulted in 92.4% and 78.9% compression of data for specimen 3 and 4 respectively. The RMS errors of the low-resolution fit for all specimens, compared with the TLS data, are shown in Table 1. However, because the fit is low resolution, key features of the crack are now represented smoothly and will necessitate a higher resolution fit at its localization. Similarly, Figure 7 (b), Figure 7(c) and Figure 7(d) show the low resolution fit results for specimens 2, 3 and 4, respectively and Table 1 shows the summary of the quantitative results for the low-resolution fit for all four specimens.

<table>
<thead>
<tr>
<th>Specimen number</th>
<th>Original number of data points</th>
<th>Low-resolution number of nodes</th>
<th>Data compression (%)</th>
<th>Low-resolution RMS error (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7954</td>
<td>27</td>
<td>99.4</td>
<td>2.8</td>
</tr>
</tbody>
</table>
The number of wavelet selected for the low-resolution fit was automatically obtained after a minimal pre-tuning of the network’s parameters. Note that minimal pre-tuning was required to achieve desirable results due to the single hidden layer of our NN architecture. A study was conducted on the accuracy of the representation as a function of the number of nodes in the
network for specimen 1, by changing parameter \( \lambda \) while keeping all other network parameters constant. The accuracy was measured in terms of the RMS error. Figure 8 is a plot of the RMS error as a function of the number of nodes. It also shows the relative computing time versus the network size. Results show a region in which the algorithm provides an optimal representation in terms of RMS error. This optimal representation occurs with 27 nodes. The decrease in performance for a higher number of nodes can be attributed to the other network parameters becoming highly 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, as expected. Note that the nodes in this study are automatically generated using the SOM theory and depend on parameter \( \lambda \).

![Figure 8: RMS error and relative computing time versus the wavelet network size.](image)

### 3.2 Crack Localization

The spatial resolution of the low-resolution surface fit is used to detect cracks, based on the principle that a crack will provide a discontinuity in the surface, therefore necessitating higher resolution of nodes around the discontinuities. Using a grid search method, the 2-norm of the wavelet bandwidths \( \| \sigma \| \) are computed, and a discontinuity is identified if the bandwidth falls below a threshold. This technique is illustrated in Figure 9 (left), where the average nodal bandwidths are plotted over the \( x-y \) grid. Blue and dark blue areas indicate a higher concentration of wavelets, while green to red represent lower concentration of wavelets. For specimen 1, a crack region is localized at the \( x \) and \( y \) points for which the wavelet bandwidths fall under the average bandwidth value \( \| \sigma \| < 0.5(\max(\| \sigma \|) + \min(\| \sigma \|)) \), as illustrated in Figure 9(a) (right) by the black rectangular area. The black rectangular region is generated by averaging the four individual sides of the colored region. While this technique preserves information on salient damage, it results in filtering out some features that may be of interest. Other techniques enabling the automatic identification of damaged areas will be studied in future work. The figure also shows the true crack region (red trapezoidal and rectangular region), demonstrating that the algorithm can be successfully used to detect a crack and estimate its location. Remark that this detection and localization was achieved regardless of the
curve in the concrete specimen, which could have been mistaken for damage if the algorithm was based on nodal weights (value of z-axis). For specimen 2, the location of cracks is determined at the x and y points where the bandwidth values are under $||\sigma|| < 0.55(\max(||\sigma||) + \min(||\sigma||))$. A slightly larger value for the gain (0.55 instead of 0.50) was used for specimen 2 because the two difference cracks present in one data set, one was a thin hairline crack barely captured by the low-resolution fit. For implementing this method in the field, the automation of the gain selection would need to be addressed. Figure 9(b) (right) shows the true crack location of the first crack (red trapezoidal region) and the second crack (red rectangle region) of specimen 2. Similarly, the values of the wavelet bandwidth associated with the localized region of the crack in specimen 3 fall under $||\sigma|| < 0.5(\max(||\sigma||) + \min(||\sigma||))$. Figure 9(c) (right) shows the location of this crack. Negligible differences in the $||\sigma||$ values resulted in the failure of estimation of crack location for specimen 4, as shown in Figure 9(d). An explanation for the failure to estimate the crack location of specimen 4 is that the depth of the hairline crack is very shallow (about 1 mm). The algorithm had no issues in determining the crack location for a deeper crack (about 4.5 mm) example seen in specimen 3. It is possible that the thin cracks in specimens 2 and 4 may not require any repair attention at the present condition.

(a) Specimen 1

(b) Specimen 2
3.3 High-resolution Fit

Once the location of a crack is localized, a higher resolution fit can be conducted around its region. For specimen 1, this region consists of 1644 data points, as plotted in Figure 10(a). To provide a better surface fit, the data is rotated to optimize the uniqueness of the $z$ values, in particular for $18 \text{mm} < x < 21 \text{mm}$. The angle between the average values of $z$ at $x = 9 \text{ mm}$ and $x = 25 \text{ mm}$ is automatically calculated as 45°. Figure 10(b) shows the rotated crack data. Figure 10(c) shows the high resolution compact representation of the crack obtained using 29 nodes. Figure 10(d) displays the overlap between the crack point cloud and representation. The difference between the point cloud and the fit is defined as the error. For specimens 1, 2 and 3, the low-resolution fit had an RMS error of 2.8 mm, 3.3 mm, and 1.8 mm, respectively, compared with the TLS data. In specimen 1, a high-resolution representation of the crack is achieved using only 29 nodes, resulting in a 97.1% data compression, plotted in Figure 10(c). With the high-resolution fit, the RMS error dropped to 1.8 mm, showing a 35.7% improvement. Similarly, a high-resolution fit for data for specimens 2 and 3 were obtained using 254 and 653 nodes, respectively. This resulted in 42.5% and 63.9% compression of data in specimens 2 and 3, respectively. Furthermore, the RMS errors for the high-resolution fit were 2.6 mm and 1.4
mm, which improved by 21.2% and 22.2%, respectively. The resulting RMS errors are attributable to noise present in the TLS data. Note that the RMS errors for the high-resolution fit were computed using the localized data set after the extraction of the crack information. Figures Figure 11 and Figure 12 show the point cloud of the cracked data, high-resolution representation and overlap of point cloud and representation for specimens 2 and 3. The quantitative results of the high-resolution fit for all specimens are summarized in Table 2.

Figure 10: (a) Point cloud of crack data; (b) point cloud of rotated crack data; (c) compact high-resolution representation; and (d) overlap of point cloud and representation for specimen 1.
Figure 11: (a) Point cloud of crack data; (b) compact high-resolution representation; and (c) overlap of point cloud and representation for specimen 2 (rotation of crack data was not required for this specimen).

Figure 12: (a) Point cloud of crack data; (b) compact high-resolution representation; and (c) overlap of point cloud and representation for specimen 3.

Table 2. Summary of the results of high-resolution fit for all four specimens.

<table>
<thead>
<tr>
<th>Specimen number</th>
<th>Original number of data points</th>
<th>Number of data points for crack</th>
<th>High-resolution number of nodes</th>
<th>Data compression (%)</th>
<th>High-resolution RMS Error (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7954</td>
<td>1644</td>
<td>29</td>
<td>97.1</td>
<td>1.8</td>
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<tr>
<td>2</td>
<td>1192</td>
<td>736</td>
<td>254</td>
<td>42.5</td>
<td>2.6</td>
</tr>
<tr>
<td>3</td>
<td>4461</td>
<td>3011</td>
<td>653</td>
<td>63.9</td>
<td>1.4</td>
</tr>
<tr>
<td>4</td>
<td>2706</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

4. Conclusions and Future Work

A strategy to sequentially construct a compact representation of a 3D point cloud has been presented. This adaptive wavelet neural network is 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 any type of LiDAR into a small set of functions and identify problem areas. The proposed wavelet network has been applied on four cracked cylindrical specimens. It was shown that the algorithm was capable of replacing a set of 7954 3D coordinates with a set of 27 functions for the first specimen while preserving the key features of the scan data, which included a crack. Similarly, 1192, 4461 and 2706 points were
compacted into 199, 204 and 342 wavelets, respectively, for specimens 2, 3 and 4. These four compact representations had RMS errors of 2.8 mm, 3.3 mm, 1.8 mm and 1.5 mm, but compressed memory usage by 99.4%, 72.2%, 92.4% and 78.9%, respectively. By looking at local regions of wavelets with smaller bandwidths, it was demonstrated that an automatic crack detection strategy can be employed to make further high-resolution analysis only on regions with damage. The high-resolution fit of the crack region of 1644, 736 and 3011 points were represented with a set of 29, 254 and 653 functions, respectively, for specimens 1, 2 and 3. This resulted in data compression of 97.1%, 42.5% and 63.9%, respectively. RMS errors for specimens for 1, 2 and 3 were 1.8 mm, 2.6 mm, and 1.4 mm respectively, demonstrating 35.7%, 21.2% and 22.2% improvements in the low-resolution representation. This technique was not capable of detecting a crack in specimen 4 which had a hairline, shallow crack feature. However, such damage is typically minor in concrete structures and does not require attention. The proposed technique allows for smaller memory usage, faster computational times, and accurate representations of problem areas. It was also demonstrated that the proposed crack detection strategy is capable of detecting damages on curved surfaces. Future research will investigate applying the proposed technique to data collected from an actual bridge. The developed methodology will be tested to guide a TLS real-time to construct accurate representation containing features of interest. This is possible as the network we have developed in this study is self-organizing, self-adaptive and sequential. Lastly, the sequential feature refers to the capability of the network to learn in a sequential manner, as opposed to batch processing. We built this sequential feature for real-time applications in combination with a controllable TLS.

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