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**INTEGRATED REMOTE SENSING AND VISUALIZATION (IRSV)
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-PHASE TWO-

VOLUME 3

**ADVANCED CONSIDERATION IN LIDAR TECHNOLOGY FOR BRIDGE
EVALUATION**

By

**Shen-En Chen and Haitao Bian, Department of Civil and Environmental
Engineering, Libin Bai, Department of Software and Information Systems,
and Edd Hauser, Center for Transportation Policy Studies,
University of North Carolina at Charlotte
Charlotte, North Carolina**

**Center for Transportation Policy Studies
University of North Carolina at Charlotte**

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EXECUTIVE SUMMARY

This report describes Phase Two enhancement of terrestrial LiDAR scanning for bridge damage evaluation that was initially developed in Phase One. Considering the spatial and reflectivity information contained in LiDAR scans, two detection algorithms were developed to document the extent of bridge surface damage. The first algorithm introduced in this report is based on spatial information. This algorithm can detect various damages on a bridge structure according to the extent of surface damage. Because some damage may involve deep area losses that are not along the laser line-of-sight (LOS), an experiment is conducted to find out the best location to set up a LiDAR. The two damage detection algorithms are presented and compared with scans on actual bridge damages to evaluate their effectiveness.

A further study estimated the potential of including reflectivity data to improve defect detection. The addition of reflectivity in damage diagnostics was determined to be useful for defect detection of curved surfaces. The study shows that the reflectivity of LiDAR scan could be used to support the automatic defect detection in bridge inspection by combining it with the current position-based algorithms.

A total of 88 bridges were studied during the two-year project period. Bridge scan data were analyzed using a spatial-based damage detection algorithm, which shows that the LiDAR application is a useful supplement to traditional visual inspection. Possible improvements in the future research could be achieved by optimizing existing algorithms.

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3.1 INTRODUCTION

3.1.1 Background

Highway bridges are critical components of the public transportation system and are mandated to be inspected every two years in order to ensure the public safety (FHWA 2007). Currently, highway bridges are inspected visually, however, advanced commercial remote sensing (CRS) and spatial information (SI) technologies have been applied to geospatial operation, environmental impact monitoring and even infrastructure management (Jelalian 1992). The implementation of remote sensing into bridge inspection would provide fast and reliable data collection in large scale geospatial survey (Liu et al. 2010).

Terrestrial LiDAR is a competitive solution for bridge inspection among other remote sensing technologies. LiDAR is a range measurement method and has been well used in engineering survey, structure geometric quantification, and spatial information reconstruction. Girardeau-Montaut (2005) applied LiDAR in structure health monitoring through processing the collected point cloud data for damage quantification. In this paper, 3D spatial information from LiDAR scans is the basis of the bridge inspection algorithms by using the similar approaches.

In order to conduct engineering evaluation, the bridge damage inspection should achieve the capability to generate quantified results. The documentation from LiDAR manufacturers mandate an accuracy and resolution of the LiDAR to be potentially far above the requirement for bridge application. From previous field testing experiences, some other factors have been found to influence the final scan results. The scan angle, for example, is one of the key factors that can generate unnecessary errors in damage quantification.

The research in the first part of the project essentially use the point cloud geometric (spatial) information to evaluate defects, which works with simple geometric surfaces such as flat planes or intersections of multiple-planes. Two different algorithms are designed respectively to conduct surface damage detection through the processing of LiDAR recorded scan data. The scanning angle influence is also studied in one experiment to identify the best position for an accurate LiDAR test. A substructure damage of a bridge is selected to validate these two algorithms. The results are compared and discussed as well.

Since typical LiDAR data contains the physical geometric information and the laser beam reflectivity information, the possibility of using LiDAR reflectivity to help accentuate damaged area images are also investigated to help enhance automatic damage detection. The point cloud data from scanning a flat surface, where each physical scanning point

would consists of the position information in Cartesian coordinate and the reflectivity number.

3.1.2 Research Objective

This research focuses on improving the algorithms used for bridge inspection, especially for damage detection. Towards this goal, three project objectives have been established:

- (1) To determine efficiency in damage detection algorithm.
- (2) To determine scan angle effects on damage quantification.
- (3) To determine applicability of reflectivity measurements to improve damage detection.

3.1.3 Scope of Work

A new algorithm has developed to conduct the defect detection. The research will include both spatial and reflectivity information in developing bridge inspection algorithm. Therefore, a series of experiments will be conducted to verify the effectiveness of this program.

By utilizing the LiDAR scanning technology and those algorithms, a nationwide study is carried out to evaluate this remote sensing based bridge inspection method. The objective of this research is to evaluate the application of terrestrial LiDAR technology in bridge inspection.

Totally 88 highway bridges located in North Carolina (30), Alabama (12), Florida (3), Iowa (19), New York (12), and California (12) have been inspected with this technology.

3.1.4 Report Outlines

In chapter 3.2, the newly designed special based algorithm has been introduced and presented. In chapter 3.3, the reflectivity information has been considered and implemented to the bridge damage detection, which made several improvements to the method. This technology is employed in the nationwide bridge inspection experiment, and the benefits and restrictions are talked in chapter 3.4. The rest of the report is conclusion and recommendation for future study.

3.2 LIDAR BASED BRIDGE INSPECTION ALGORITHMS

The functional objectives of bridge evaluation programs using terrestrial LiDAR scanning are to detect and quantify defects, measure bridge clearance and deformation information. Row and column numbers, relative position to the scanner, XYZ coordinate value, and raw reflectivity are the information contained in a typical LiDAR scan point (Bian 2012). The integration of all these information from the scan point cluster can be used to reconstruct the bridge surface or structure. Numerical algorithms can be developed to measure and evaluate the virtual structure model and give out the inspection results. Two algorithms are presented in this paper, which have been established for the purpose of damage detection. The critical difference between the two algorithms is the definition of reference surface that is to be used for damage area quantification.

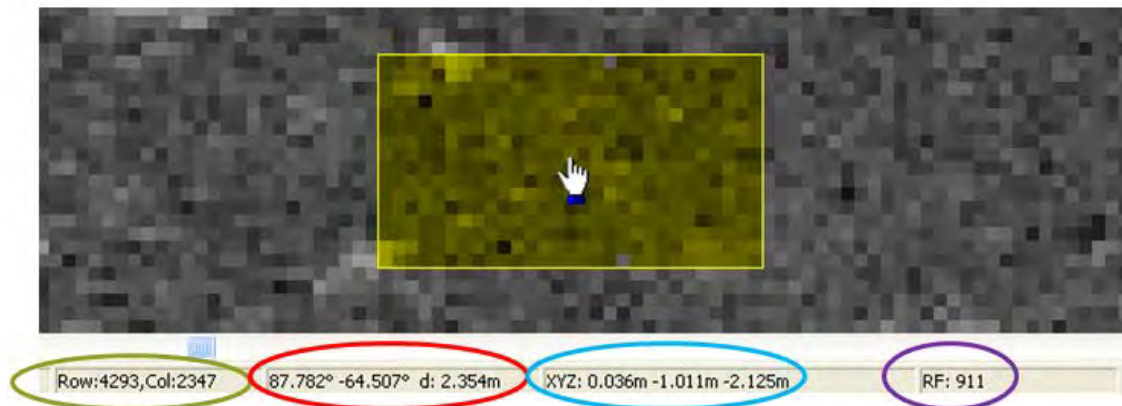


Figure 1. Information in a LiDAR scan point

3.2.1 Distance and Gradient Criterion Method

The first algorithm determines the damage portions of the recorded point cloud with a two criteria damage qualifier: distance and gradient. The algorithm is named the distance and gradient criterion (DGC) method. The first step of the DGC algorithm is to define a reference plane for the selected point cloud. The point cloud collects the surface topology information of the bridge components, and the reference plane is used to compare with the recorded data to determine whether there are some defective areas within the point cloud.

Selection of a reference plane is based on picking three edge points in a selected investigation area. The selection of the damage area is semi-heuristic, since the user must be able to select an area of questionable nature within an entire scan. Two of the three points are located on the boundary of the selected area, hence, it is very important to identify the area and they must be in a diagonal line. The third edge point is located on the upper center of the selected area. Moreover, a lower center point is used to test the

accuracy of the selection. The validity of each point is also checked by comparing their coordinate value to the surrounding scan points through a search algorithm. The selected study surface is then rotated such that it is parallel to the XY plane (horizontal plane) and then the reference plane is generated (Liu 2010).

(1) Identification of the irregular points

The points scanned from the damage area are defined as irregular points. The recognition of the defective areas is achieved by identifying the irregular scan points of the selected investigation area. The defect types in a bridge component considered in the current approach include mass loss of materials such as due to corrosion expansion and erosion breakdown that can be detected in the LiDAR scan data. Usually the scan points of the defective area will have obvious irregular coordinate values and different reflectance when compared to the surrounding surfaces.

The coordinate value differentiation between the selected scan points and the reference plane, as well as the change of gradient value of the scan points, are the two criteria used to determine whether a scan point belongs to the defective part. Since the selected investigation area has been rotated and is parallel to the XY plane, D , the distance between the scan points to the reference plane can be easily obtained as

$$D = |Z_P - Z_{REF}| \quad (1)$$

where Z_P is the Z coordinates value of the selected points, and Z_{REF} is the Z coordinate value of the reference plane.

The variation of the gradient between scan points is also a reliable criterion to determine the irregularity of a certain scan point. By referring to the nearby scan points, the gradient of a certain irregular area which has a column number C and row number R , can be represented as:

$$G = \left| \frac{Z(C+\theta, R) - Z(C-\theta, R)}{\sqrt{(X(C+\theta, R) - X(C-\theta, R))^2 + (Y(C+\theta, R) - Y(C-\theta, R))^2}} \right| + \left| \frac{Z(C, R+\theta) - Z(C, R-\theta)}{\sqrt{(X(C, R+\theta) - X(C, R-\theta))^2 + (Y(C, R+\theta) - Y(C, R-\theta))^2}} \right|, \quad (2)$$

where $X(C, R)$, $Y(C, R)$, and $Z(C, R)$ are the X, Y, Z coordinate values of the selected point within the data matrix and with column number as C and row number as R . θ is the number of points in each preset interval. The interval value can be adjusted manually to reduce the potential deviation caused by noisy data points. Usually, a value between 1~4 is used for small area defect detection, while 5~10 is suggested for larger defective area detection.

Both distance and gradient are used for irregularity check. The checked point will be regarded as an irregular point if $D > \alpha_d * D'$ or $G > \alpha_g * G'$. D' is the average distance to the reference plane and G' is the average gradient value of the entire surface. The coefficients α_d and α_g are selected based on the proportion of the total defective area to the selected investigation area. Typical values for α_d and α_g are

(2) Defective Area Quantification

To quantify a defective area, the selected study surface is divided into small grids before processing the point irregularity check. For each divided grid, there are two irregular rates, which are based on distance and gradient criteria, respectively:

$$\theta_d = \frac{N_{Di}}{N_{all}}, \text{ and } \theta_g = \frac{N_{Gi}}{N_{all}}. \quad (3)$$

where θ_d is the irregular rate based on distance criterion, θ_g is the irregular rate based on gradient criterion. N_{Di} and N_{Gi} is the number of the irregular points within the grid, N_{all} is the total number of the points within the grid. The grid will be considered as a defective grid when both the distance and gradient irregular rates have exceeded the predefined values. In this paper, the thresholds of both distance and gradient irregular rates to judge the defect are set as 0.5.

Once a grid is determined as a defective grid, its surrounding grids will also be checked to see if they are defective parts as well. If one of the eight grids is also regarded as a defective part, the same procedure will be applied to its surrounding grids until all of the involved grids have been checked.

The defect area can be quantified after all the grids were checked according to the defect identification criterion defined previously. The area and volume of the whole defective portion can be calculated by adding up the area and volume of each defective grid. For example, volume is computed as:

$$V = \sum_{i=1}^N (A_i * \bar{D}_i * \theta_i), i = 1, \dots, N. \quad (4)$$

where A_i is the defect area of the grid i , $\bar{D}_i$ is the average distance of the grid i points to reference plane, and θ_i is the irregularity rate of grid i .

3.2.2 Mean Sum Error and Triangulation (MSE&T) Method

The second damage detection algorithm is based on MSE and Delaunay triangulation. In the MSE&T method, regression is used to find an optimal reference plane with the least MSE. Moreover, the reference plane could also be assigned manually by selecting several cloud points in the undamaged bridge surface in this algorithm.

(1) Calculate the reference plane

The first step of the MSE&T method is to identify a linear reference plane for the selected investigation area. The reference plane refers to what the good surface should be, and the entire area will be compared to the reference plane to identify the defect. Figure 2 depicts the linear regression with the minimum MSE method.

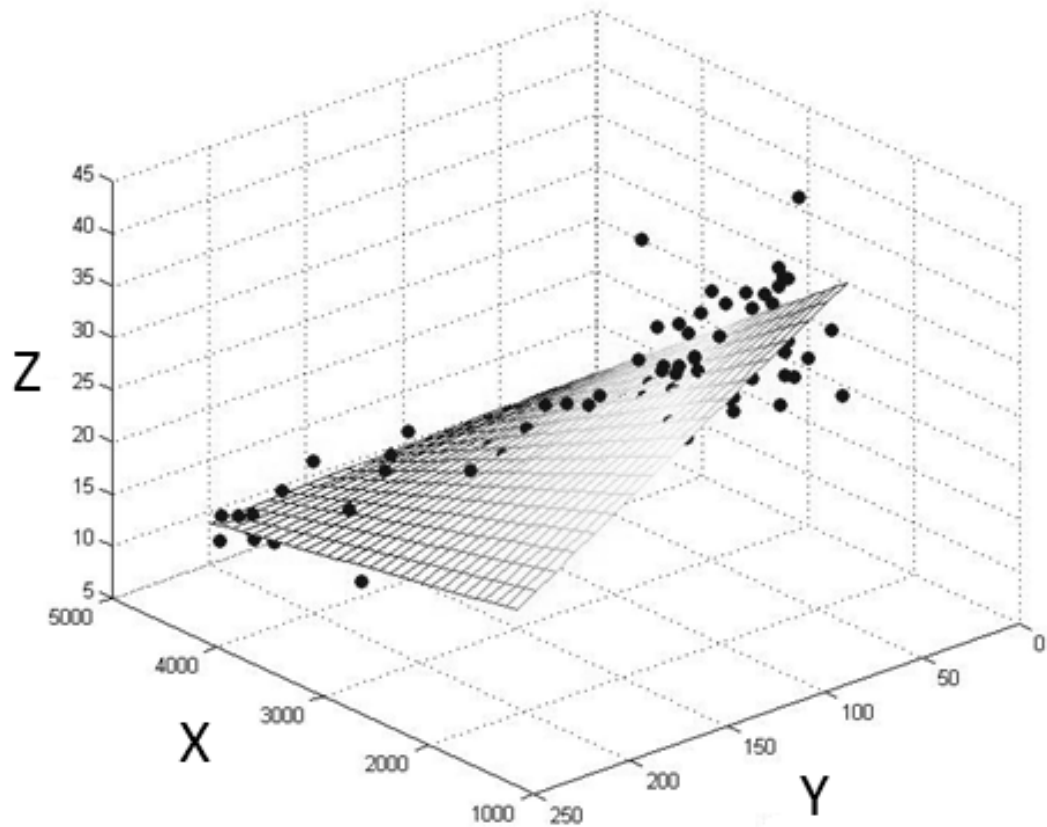


Figure 2. The formation of a reference plane using MSE regression

In the three dimensional space, only one plane exists with a minimum MSE for the given point cloud cluster with more than 3 points. The MSE&T method requires the selection of as much undamaged area as possible to make the reference plane close to the normal surface. The MSE of a point cloud is defined as follow:

$$MSE = \frac{\sum_{i=1}^n (d_i)^2}{n}, \quad (5)$$

where n is the number of the selected cloud points, and d_i is the distance of point i to the reference plane ($i = 1, \dots, n$, respectively)

In order to calculate the reference plane with minimum MSE, a regression model is defined as:

$$z_i = b_0 + b_1x_i + b_2y_i + \varepsilon_i, i = 1, \dots, n, \quad (6)$$

where $[x_i \ y_i \ z_i]$ is the coordinate of point i , and ε_i is the error, which is the signed distance to the reference plane. z_i is the dependent variable and x_i and y_i are the independent variables. ε_i has the following relationship with the distance d_i :

$$d_i = |\varepsilon_i|, \quad (7)$$

The parameters of (b2), i.e., $B = [b_0 \ b_1 \ b_2]'$, calculated from those two independent variables regression are applied to determine the reference plane which can be represented as follow:

$$b_1X + b_2Y + Z + b_0 = 0, \quad (8)$$

The entire point cloud is mapped to a new coordinate system to simplify the calculation. In the new coordinate system, the defined reference plane is parallel to the X-Y plane, and the cloud point is defined as $[x_t \ y_t \ z_t]$. The reference plane in the new coordinate frame is represented as $[x_t \ y_t \ 0]$. There are three steps to make the coordinate transformation:

The parameters of the calculated reference plane are first normalized as.

$$\begin{bmatrix} m \\ n \\ k \\ j \end{bmatrix} = \begin{bmatrix} b_1 / \|[b_1 \ b_2 \ 1]'\|^{1/2} \\ b_2 / \|[b_1 \ b_2 \ 1]'\|^{1/2} \\ 1 / \|[b_1 \ b_2 \ 1]'\|^{1/2} \\ b_0 / \|[b_1 \ b_2 \ 1]'\|^{1/2} \end{bmatrix}, \quad (10)$$

where $[m \ n \ k]'$ is the normalized norm vector. j is the distance from $(0, 0, 0)$ to the reference plane in the new coordinate system.

Then a matrix T is defined to perform the transformation:

$$T = T_1 T_2 T_3$$

and,

$$T_1 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ jm & jn & jk & 1 \end{bmatrix},$$

$$T_2 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \frac{k}{(n^2+k^2)^{1/2}} & \frac{n}{(n^2+k^2)^{1/2}} & 0 \\ 0 & \frac{-n}{(n^2+k^2)^{1/2}} & \frac{k}{(n^2+k^2)^{1/2}} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$$T_3 = \begin{bmatrix} (n^2 + k^2)^{1/2} & 0 & m & 0 \\ 0 & 1 & 0 & 0 \\ -m & 0 & (n^2 + k^2)^{1/2} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \quad (11)$$

Matrix T_1 transforms the calculated reference plane to $[0 \ 0 \ 0]$ point, while T_2 and T_3 are the rotation and scaling matrixes.

In the last step, the transformation will expand the coordinate of point i from $[x_i \ y_i \ z_i]$ to $[x_i \ y_i \ z_i \ 1]$, and get the transformed coordinate value $[x_{ti} \ y_{ti} \ z_{ti} \ 1]$ of point i by:

$$[x_{ti} \ y_{ti} \ z_{ti} \ 1] = T[x_i \ y_i \ z_i \ 1], \quad (12)$$

Then remove element “1” from $[x_{ti} \ y_{ti} \ z_{ti} \ 1]$ to get the transformed coordinate value $[x_{ti} \ y_{ti} \ z_{ti}]$.

(2) Defect identification and quantification

MSE&T method uses the distance from scan points to the reference plane as the criterion to identify the defective parts. Therefore, a pre-determined tolerance value needs to be manually assigned before detecting the defective areas. Each point i with $|z_{ti}| > |tolerance|$ is considered as a defect point.

Since the point has no area or volume attributes, defective triangle is introduced to quantify the area and volume of the defect. The Delaunay triangulation algorithm (Delaunay 1934) can link the scattered scan points to a surface consisted of multiple triangles .

The steps to get a smooth surface are described as follows:

Firstly project each point $[x_{ti}, y_{ti}, z_{ti}]$ of the selected investigation area to the X-Y plane as showed in Figure 3.

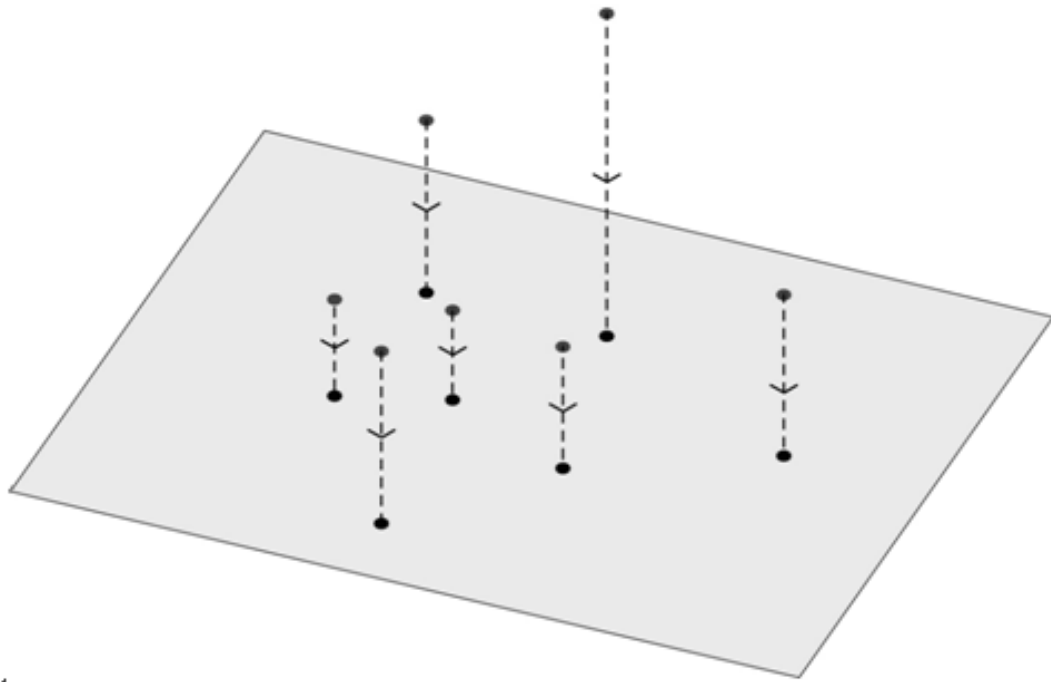


Figure 3. The projection of spatial cloud points to the plane

After that, the Delaunay's triangulation algorithm is used to aggregate the projected points on X-Y plane into non-overlapping triangles as showed in Figure 4.

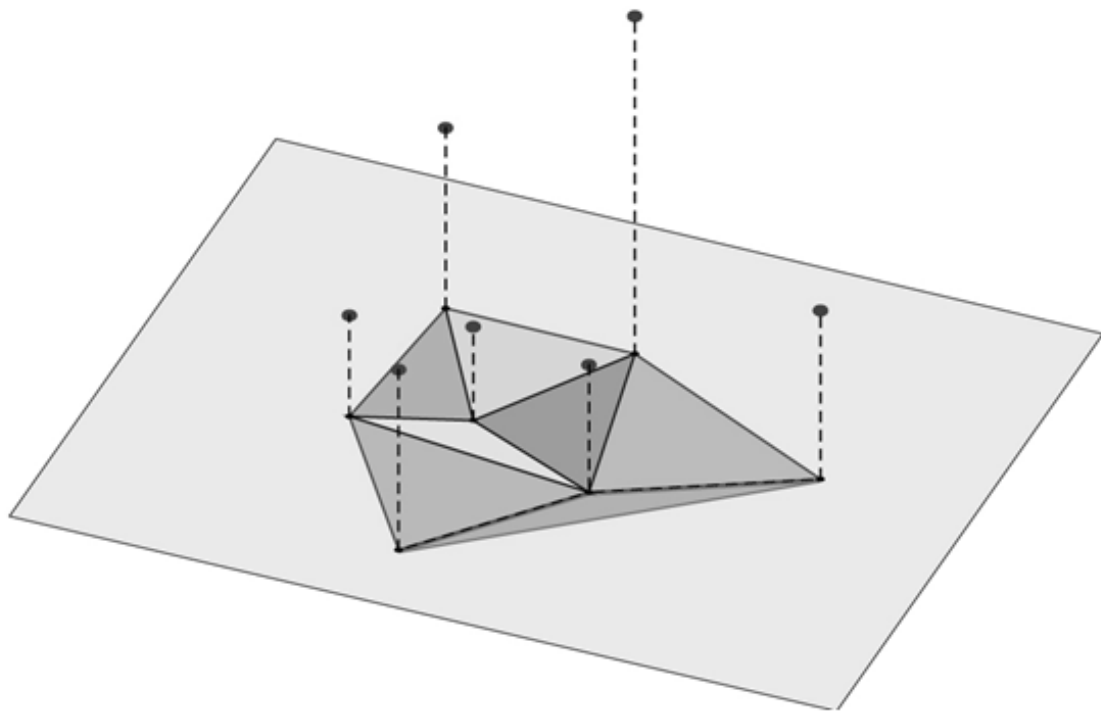


Figure 4. The generation of triangles using Delaunay's triangulation algorithm

In the last step, assign the z value back to the projected point set, which forms a 3D surface with the triangles created in the second step. The triangulation of the cloud points and the formation of surfaces in the three dimensional space are shown in Figure 5.

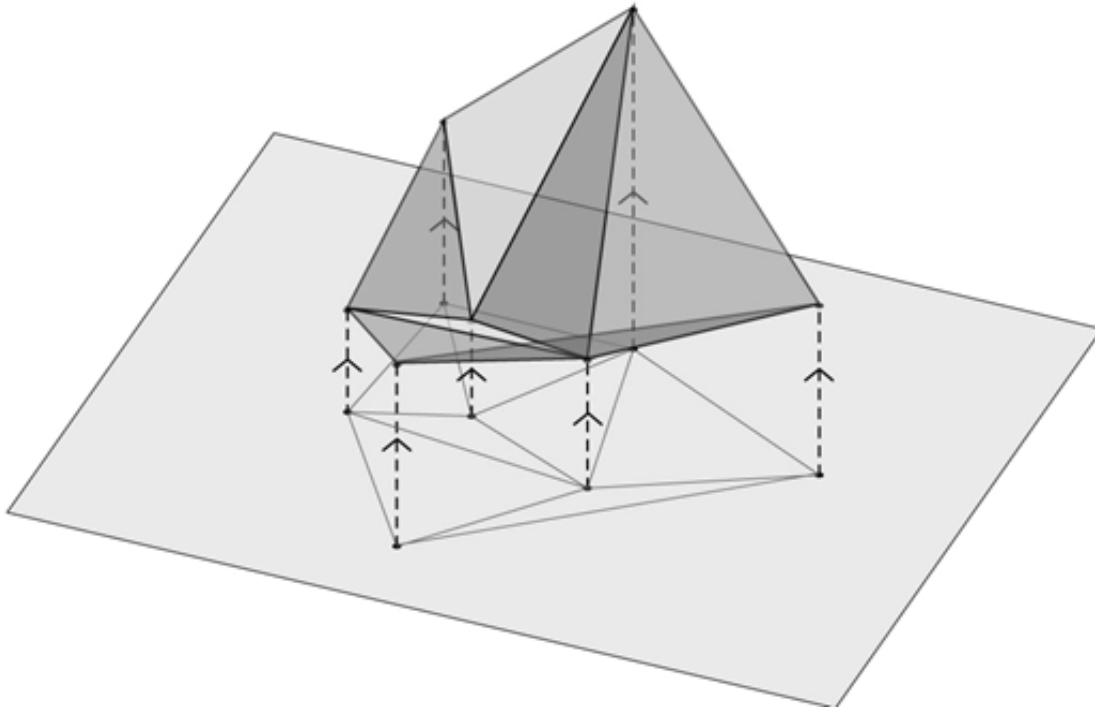


Figure 5. Assign the z value back to the projected point set

The defective area sums up the area of all the projected triangles in the reference plane, and the defective volume is calculated by multiplying the area of defective triangle and the average distance of the points to the reference plane.

3.2.3 Experiment and Data Analysis

The damage detection and other LiDAR algorithms developed so far can provide bridge engineers fast and accurate inspection tools, and these programs can be automated to reduce time during inspection. Two experiments have been conducted to validate the two algorithms.

The accuracy of the damage detection is very important to the bridge inspection. Generally, the result can be influenced by both the process of point cloud acquisition and the effectiveness of the algorithm. The differentiated results caused by the application of the two different algorithms are discussed during an experiment of damage detection for a highway bridge. Factors that might affect the result of the LiDAR scanning may include

angular, and edge effects, as well as surface reflectivity, etc. Current report will focus on the scanning angle influence to the result which is related to the angular accuracy.

(1) Evaluation of influences by different scanning angles

The following experiment was designed and carried out to study the influence of scan angel of the object to the damage detection and quantification result. To simulate the flat damage surface, a shipping box with a rectangular hole (Dimension: $0.09m*0.09m*0.05m$) is used in the experiment. The top area of the hole is $8.10E-03m^2$ and the entire volume is $4.05E-04m^3$.

The surface of the shipping box has been scanned three times with the hole placed opposite to the scanner at three different positions. The surface of the shipping box is similar to the bridge components surface, which is not exactly flat. Table 1 shows the computed scan results from DGC and MSE&T method respectively.

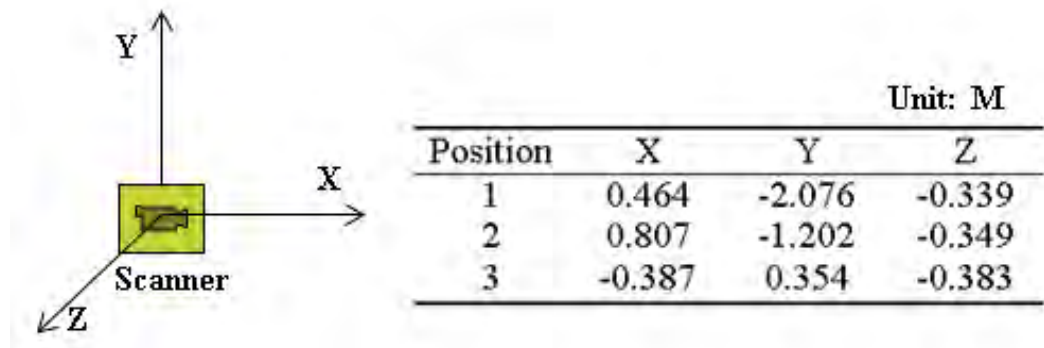


Figure 6 . The animation of the three different scan positions

Table 1. Quantification of scan angle effect using DGC Method

Point	Area	Error Rate	Volume	Error Rate
1	9.67E-03	19.4%	4.62E-04	14.1%
2	9.17E-03	13.2%	4.54E-04	12.1%
3	8.42E-03	4.0%	4.30E-04	6.2%



Figure 7. The detection results for different scan points using DGC Method.

The 3D reconstruction of the experiment result scanned from the three different positions processed using DGC method (see Figure 7). It is obvious that some edge areas of the rectangular are also counted as damage parts in all of the three scans, which makes the quantified areas of the rectangular bigger than the designed value. That is because the partial scan of the damage cannot provide a clear edge of the hole due to insufficient scan points. The partial scan will also influence the quantification of the volume for the oblique scan cannot capture the entire shape of damage.

Table 2. The quantification of scan angle influence using MSE&T method

<i>Point</i>	<i>Area</i>	<i>Error Rate</i>	<i>Volume</i>	<i>Error Rate</i>
1	9.48E-03	17.0%	4.55E-04	12.3%
2	7.90E-03	2.5%	4.18E-04	3.2%
3	8.14E-03	0.5%	4.01E-04	1.0%

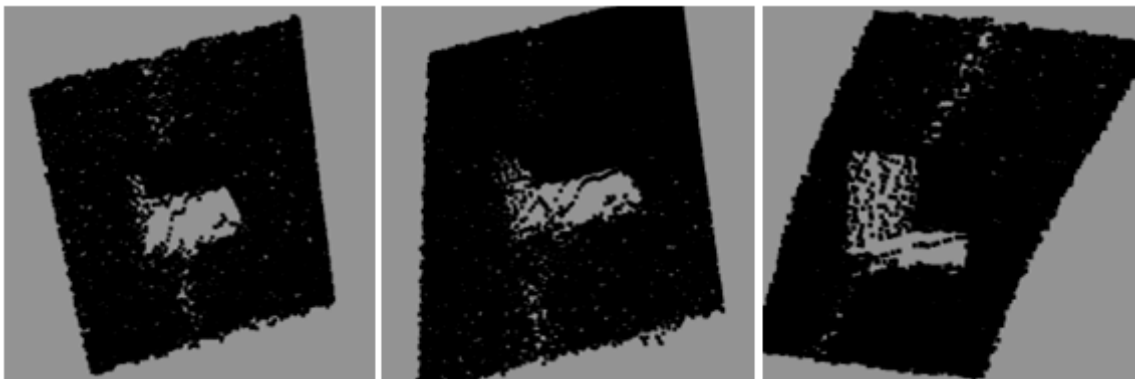


Figure 8. The detection results for different scan points using MSE&T method

The 3D reconstruction of the experiment result scanned from the three different positions processed using MSE&T method (is shown in Figure 8). It could be easy recognized

from the figures that some scanned (light colour) points in the middle of the sample are as the damage points. That also increased the value of area and volume of the damage.

Theoretically, accurate quantification of a damage portion of bridge components needs sufficient and useful scan points. If the LiDAR scanner was not placed right opposite to the damage, it will possibly cause some error to the result as showed in this experiment. Therefore, the selection of scan points in the bridge inspection is very important when conducting the LiDAR scanning.

(2) Case Study: Bridge 924145 in Florida

A segment of a 5-span concrete bridge, constructed in 1983, is being studied. A LiDAR scan was conducted on the surface of the bridge with a focus on cracking and deterioration located at one of the expansion joints.

The damage along the surface can be seen in Figure 9. The damage selected is a typical mass loss of material on concrete bridge deck surface. In this particular case, the damage is seen to spread from the deck joint. The scan is performed using Faro LS880 LiDAR scanner. The point cloud data is then used to detect and quantify the damage along with the two algorithms presented.

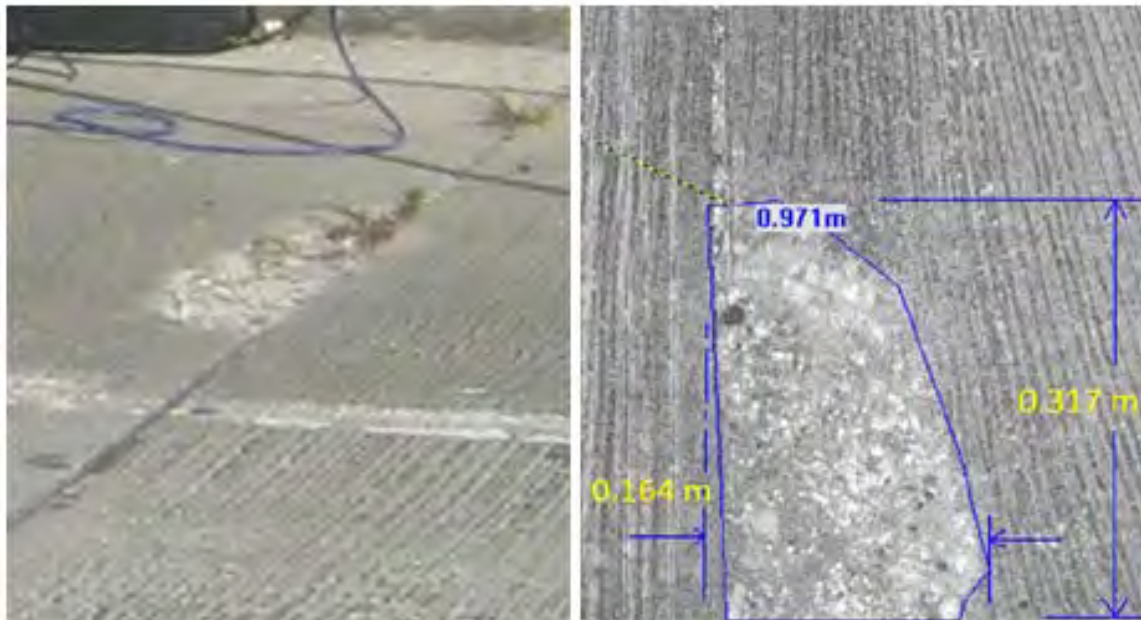


Figure 9. The mass loss of material damage on Bridge 924145

Both DGC and MSE & T methods output the defective points and the undamaged points separately. Figure 10 shows the result of the damage detection using the DGC algorithm. The colored points in the picture are recognized as defective portion and the dark grey points are regarded as undamaged portion. The defective points are can be distinguished from the undamaged points by color. For MSE & T method, the plane composed by the small grid lines is the defined reference plane by the algorithm. The white concave portion is the damaged part of the selected study surface. The damage quantification results from both methods are given in Table 3.

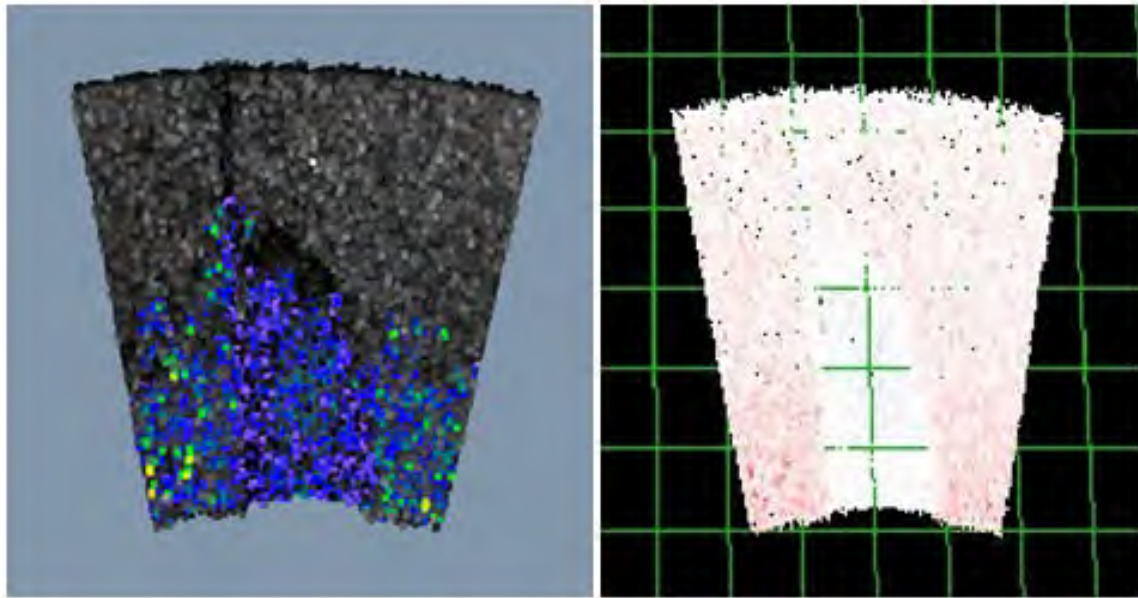


Figure 10. Displays of damage detection using DGC and MSE & T methods

Table 3. The comparison of the results obtained by the two damage detection algorithms

<i>Program</i>	<i>Area</i>	<i>Volume</i>
<i>DGC</i>	<i>7.73E-02</i>	<i>1.98E-03</i>
<i>MSE&T</i>	<i>7.25E-02</i>	<i>2.05E-03</i>

(3) Case Study: Bridge 590147 in Florida Bridge



Figure 11. The LiDAR scan result of the damage

590147 has also been selected to evaluate the effectiveness of the two algorithms. The substructure showing distress in pile cap, and there comes three part of material loss damage parts. The LiDAR scan was conducted underneath the bridge (See Figure 11).

The DGC method outputs the defective points and the undamaged points separately. Figure 12 shows the result of the damage detection using the DGC algorithm. The damage quantification results from both methods are given in the following Table 4.

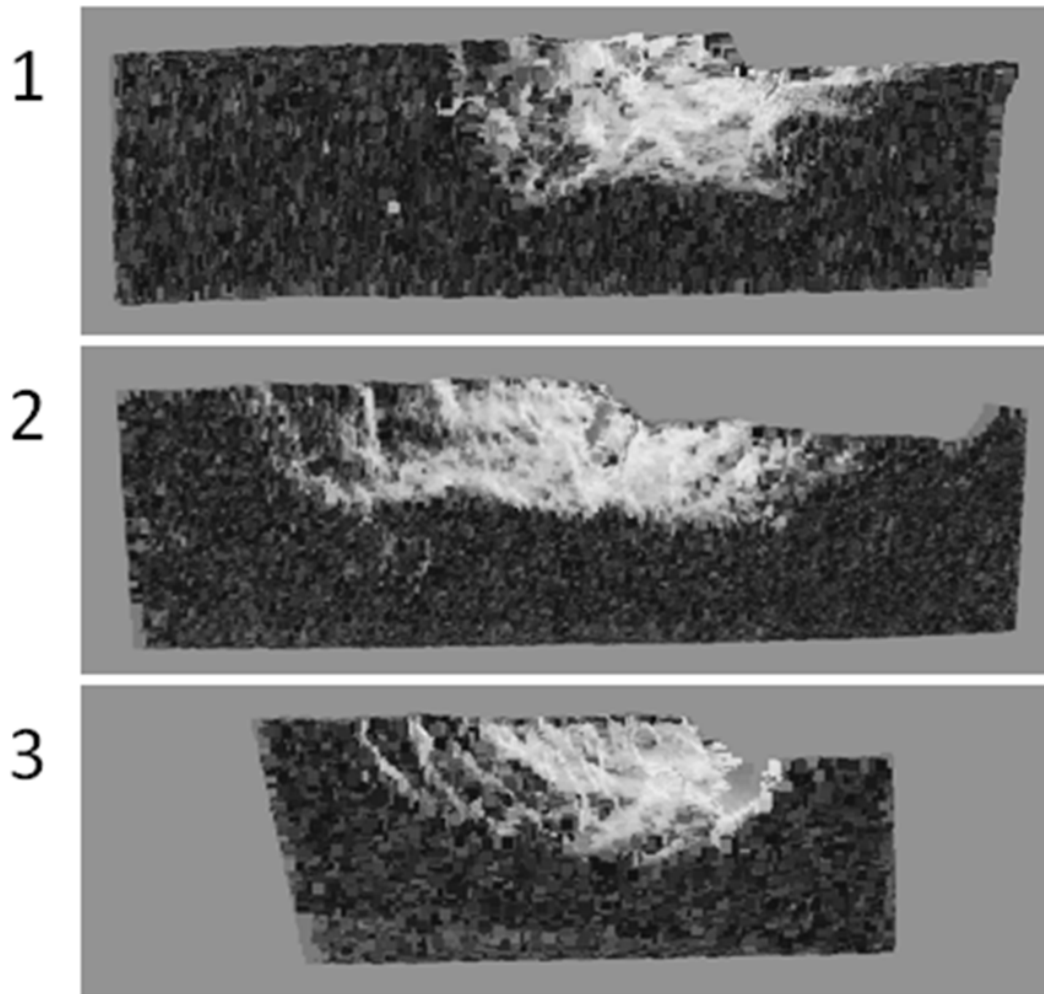


Figure 12. The reconstruction of damage detection result (DGC)

Table 4. Damage detection results obtained by DGC and MSE&T algorithms

<i>Algorithm</i>	<i>DGC</i>		<i>MSE&T</i>	
<i>Damage</i>	<i>Area</i>	<i>Volume</i>	<i>Area</i>	<i>Volume</i>
1	1.38E-01	1.61E-02	1.44E-01	1.73E-02
2	1.77E-01	1.26E-02	1.78E-01	1.26E-02
3	1.34E-01	1.23E-02	1.38E-01	1.31E-02

The results indicate that the two methods are very close in the quantitative values for both area and volume calculations. Furthermore, both methods are highly relying on the selection of reference plane as well as damage criteria. The errors mainly due to the differences in the reference plane selection as well as the linkage of the scatter scan points to smooth spatial surfaces. Since the MSE & T method uses a straight reference plane, the quantified area is more clearly defined and specific. The DGC method, being discrete, is more likely to quantify an arbitrary area, where specific damage boundary blurs out near the edges.

3.2.4 Summary

In this report, two different algorithms are presented which could process terrestrial LiDAR scanning to identify bridge surface damages. The scan angel influence to the inspection result is also considered and come out the suggesting for scanner placement in the field test. The material loss damage underneath a concrete bridge deck is selected to validate the LiDAR damage evaluation program. The result in the experiment shows that with a proper setting of the scanner position can minimize the error caused by scan angel influence, and the LiDAR scanning technology can be used to detect damages effectively in concrete bridge components.

3.3 BRIDGE DEFECT DETECTION USING LIDAR REFLECTIVITY

3.3.1 LiDAR Reflectivity Study

Reflectivity value of a laser beam is essentially the light intensity (reflectance) recording of the returning beam and is a function of the target surface quality, reference beam modulation technique and the electronic phase delay. Since different surfaces may generate different reflectivity data, the reflectivity values may help accentuate damage locations.

A closer look at a single scan point, the following information is usually collected: row and column number, polar coordinates, Cartesian coordinates, as well as reflectivity value. Hence, assume a scanned data set has n points, then, the set could be described as:

$$P = \begin{bmatrix} x_1 & y_1 & z_1 \\ x_2 & y_2 & z_2 \\ \vdots & \vdots & \vdots \\ x_n & y_n & z_n \end{bmatrix}, \text{ and } R = \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_n \end{bmatrix}. \quad (1)$$

where P is the Cartesian coordinates of the scan points, which take into account of the placements of the scanner within the coordinate system. R is the reflectivity value where darker scan points are usually associated with small reflectivity values, while brighter scan points are associated with higher values. According to the Phong reflection model, the surface reflects light as a combination of ambient, diffuse, and specular reflections. The light intensity actually equals to the total intensity of all three types of reflection. In a typical LiDAR survey, the ambient reflection is usually assumed to be outside of the range for consideration, thus the reflection model can be represented as:

$$I_r = I_d + I_s, \quad (2)$$

where I_r is the observed reflection intensity, I_d is the diffuse reflection intensity, and I_s is the specular reflection intensity.

Previous attempts to establish automated damage detection instead of relying on human observations during bridge inspection are based on photography imaging technique, where image processing and other pattern recognition techniques are regarded as the most promising methods in surface crack identification and defect detection: Oliveira (2009) introduced an integrated two line scan, high-speed cameras and a laser system for automatic crack detection and classification using survey images acquired in a high speed vehicle. The damage extraction approached used in the automated system is essentially relying on the camera shots. To automate the determination of deterioration level during bridge inspection, Abdel-Qader et al. (2003) compared four different edge detection techniques for crack identification and recognized that Fast Haar Transform (FHT) is

more reliable than the other three (directional morphology, directional second order Gaussian derivatives, and Hough transform).

LiDAR reflectivity has been used by Maas et al. (1999) for building outline differentiation from surrounding trees, but not for damage detection.

The processing of LiDAR reflectance value is similar to photographic image processing, and the statistic characteristics of reflectivity data acquired from different areas on the bridge surface can be used to indicate the bridge conditions. A sample scanned area on a bridge deck is selected to illustrate the differences in reflectivity on the bridge surface. Figure 13 shows a bridge deck pavement that includes asphalt road surface, roadway painting, and a crack zone. By analyze the histograms of the reflectivity values from those three surface types, the differences of the histogram distribution can be easily identified. The reflectance value of a perfect asphalt-covered area has a uniformly distributed pattern that can be assumed to be normal distribution. The reflectance value of paint on the bridge surface is more inclined to the right side of the histogram (lope-sided distribution). The reflectance value of asphalt with cracks has a near normal distribution, but the distribution is not as smooth as the undamaged asphalt areas indicating cracking can cause dispersion of intensity.

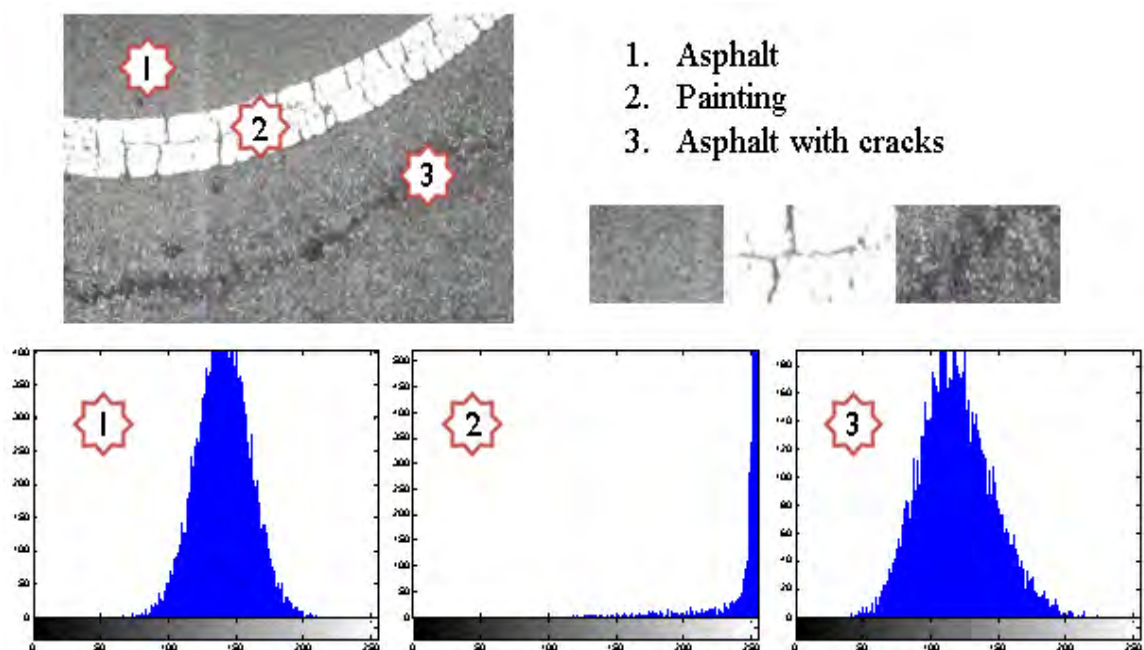


Figure 13. Histograms of the reflectance values of three different bridge surface types

3.3.2 Defect Detection using LiDAR Reflectance data

The defect detection system proposed in this paper is implemented into five correlative processes. The following chart (Figure 14) demonstrates the pre-processing of the selected LiDAR data, filtration of noise within the data, division of image information into blocks for separate image processing, and finally the identification of the defective area/areas. The following sections describe in detail each of the processes.

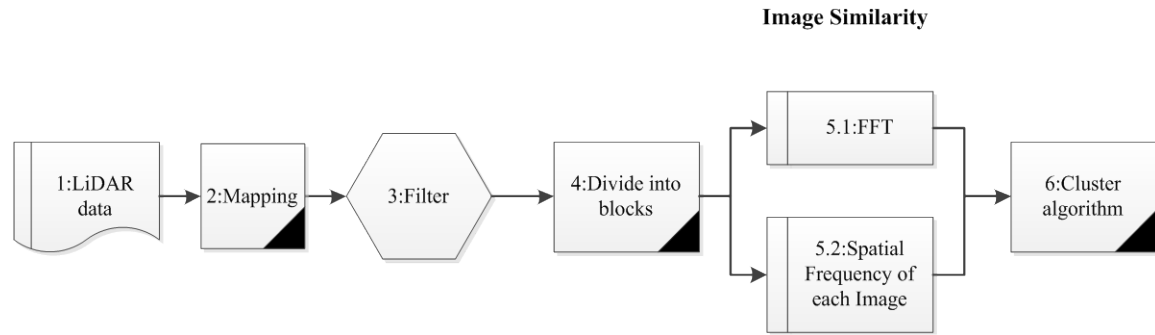


Figure 14. Diagram of the automatic processing program

(1) Mapping

For a selected LiDAR scan data (point cloud), it is assumed that only one plane with the minimum Mean Square Error (MSE) exists in the three dimensional space. The MSE of the point cloud is defined as:

$$MSE = \frac{\sum_{i=1}^n (d_i)^2}{n}, \quad (3)$$

where n is the number of the selected cloud points, and d_i is the distance of point i to the reference plane ($i = 1, \dots, n$, respectively).

The regression model is used to calculate the reference surface, which indicates where the undamaged surface should be and the entire selected area is then compared with this generalized plane to identify the defective areas. Hereafter, the entire LiDAR data is then mapped to a new coordinate system to simplify further calculations. In the new coordinate system, the defined reference plane is treated to be the new X-Y reference plane, and the coordinate of each scan point $[x_i \ y_i \ z_i]$ is then transferred to $[x_t \ y_t \ z_t]$ – mapping mechanism.

(2) Filter

The filter in the reflectivity-based defect identification system is similar to other pre-processing algorithms in image processing. This operation is aimed to remove noise data points, including those with an extremely large Z value. Noisy data can occur when the

laser energy is scattered due to surface irregularity. The minimum value of $\bar{z}_l$ is then assigned to zero. All data points are then shifted relative to the value change of the minimum value of $\bar{z}_l$, and the values of $\bar{z}_l$ are scaled to 0~255. The filter algorithm is then used to create a certain size bitmap, and assign the gray scale value of $\bar{z}_l$ to the corresponding $(\bar{x}_l, \bar{y}_l)$.

(3) Divide into Blocks

The bitmap is divided into a series of adjacent cells, and the amount of pixel blocks within each cell should equal to the exponential function of integer 2 as 2^m .

(4) Reflectivity Data Processing

The Fast Fourier Transformation (FFT) is an important image processing tool, which is used to decompose an image into its harmonics (sine and cosine components). In the digital image processing, the FFT is typically for the Discrete Fourier Transform (DFT) and the inverse DFT as an optimized computational algorithm. The input image is typically considered to be the spatial domain equivalent, while the output of the transformation represents the image in the intensity spectral domain.

For an image of size M*N, the two dimensional (2D) DFT is given as:

$$F(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m, n) e^{-i2\pi(x\frac{m}{M} + y\frac{n}{N})} \quad (4)$$

where $f(m, n)$ is the reflectance value of the pixel at coordinates (m, n) , $F(x, y)$ is the value of the reflectance image in the frequency domain corresponding to the coordinates x and y , and M and N are the dimensions of the image.

Figures 15 show the image data for cell images with and without defect respectively. The data analysis indicates that the spectrum of the LiDAR reflectivity data of undamaged pavement surface is almost close to the Gaussian white noise, while for the defective areas, it appears to have larger value with low frequent signal in the spectrum.

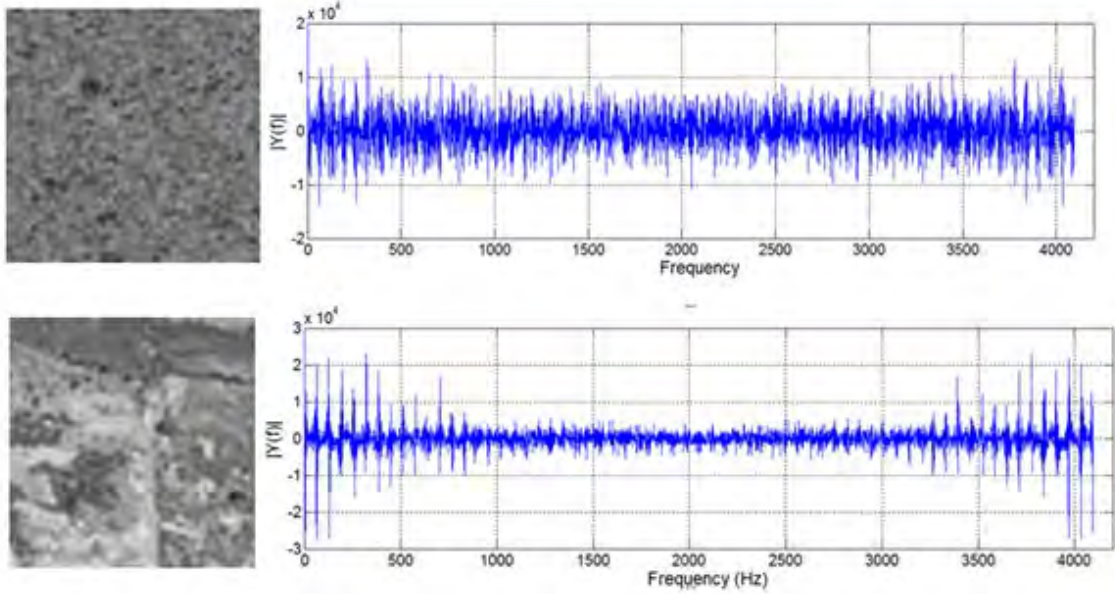


Figure 15. Cell without and with defect and its spectrum comparison

The characteristic value picked from the FFT is the amplitude of the largest value on the left image, which is denoted as C_l^{FFT} , for the cell l .

The histograms of cells without defect are similar to each other (with a narrow band distribution) as indicated in Figure 16, while the patterns of histograms from defective portions are more irregular in shapes. The reflectance value range (0 to 2047) of the LiDAR scan data has been scaled from 0 to 255.

The characteristic value C_l^{hist} , selected from histogram is:

$$C_l^{hist} = \frac{W_l}{V_l} \quad (5)$$

where V_l is the amplitude value and W_l is the width of the largest bump of cell l .

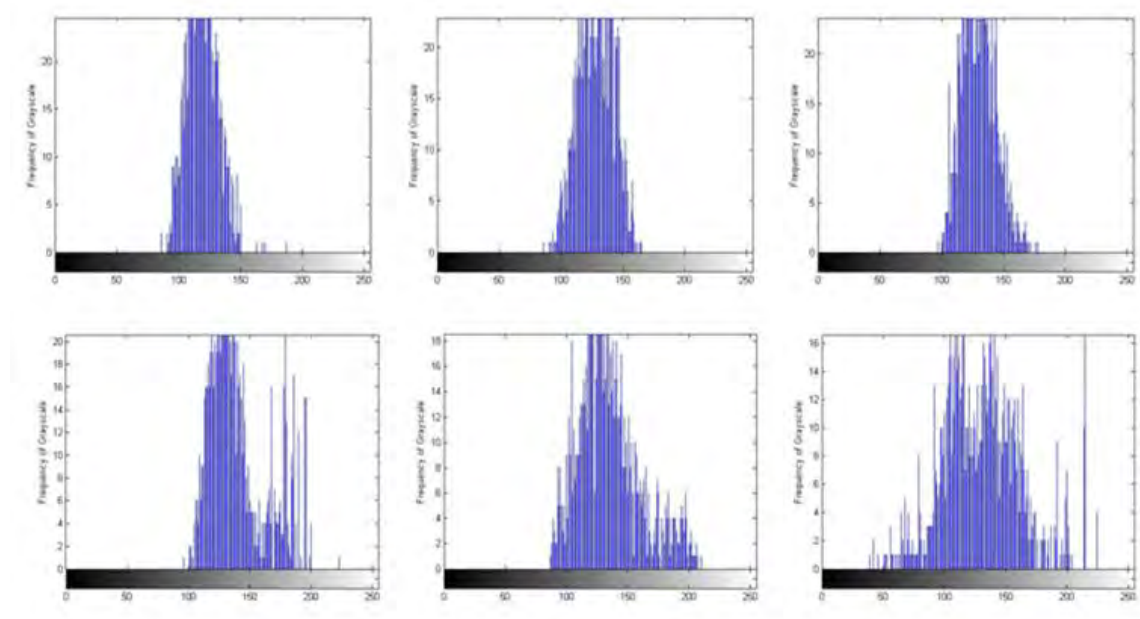


Figure 16. Histograms of the cells reflectivity without and with defects

(5) Cluster Algorithm

Finally, the cluster algorithm is used to quantify damage by classifying each cell based on its pair of characteristic values (C_l^{FFT}, C_l^{hist}). In this paper, the K-means clustering algorithm between intensity histogram and 2D FFT spectral data is used to group the characteristic pairs. The K value will be increased if it does not fulfill the tolerance for error.

3.3.3 Data Analysis

An experiment was carried out on collected bridge deck images using a damaged deck joint area (Figure 17) and a reinforced concrete beam (Figure 19), both of which have damaged portions. The algorithm, described in previous section, is used to quantify the damages. The defect identification algorithm first applies the filter to remove the unnecessary noises of the data, and scale the reflectance value to the range of 0~255. Then the scanned data is divided into different individual cells. Each of the divided cells is transformed and represented in frequency domain. For LiDAR applications, the number of frequencies in the frequency domain is equal to the number of reflectance value in the scan data or spatial domain.

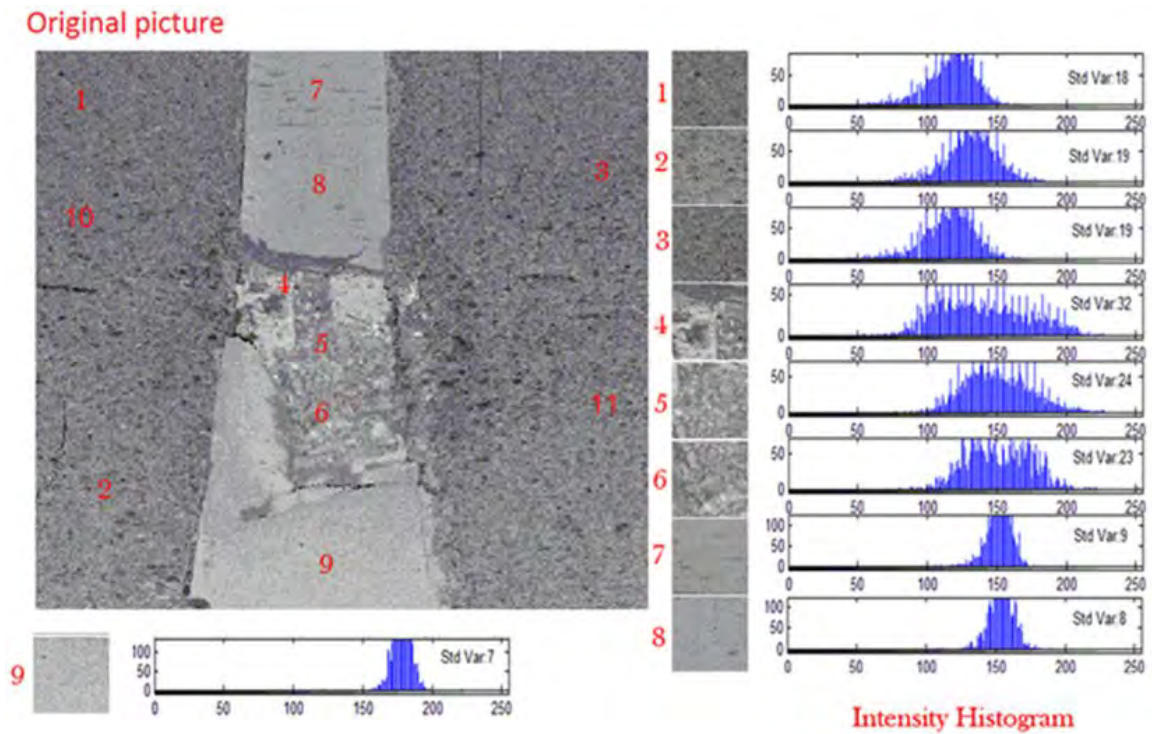


Figure 17. Joint damage identification using reflectivity data

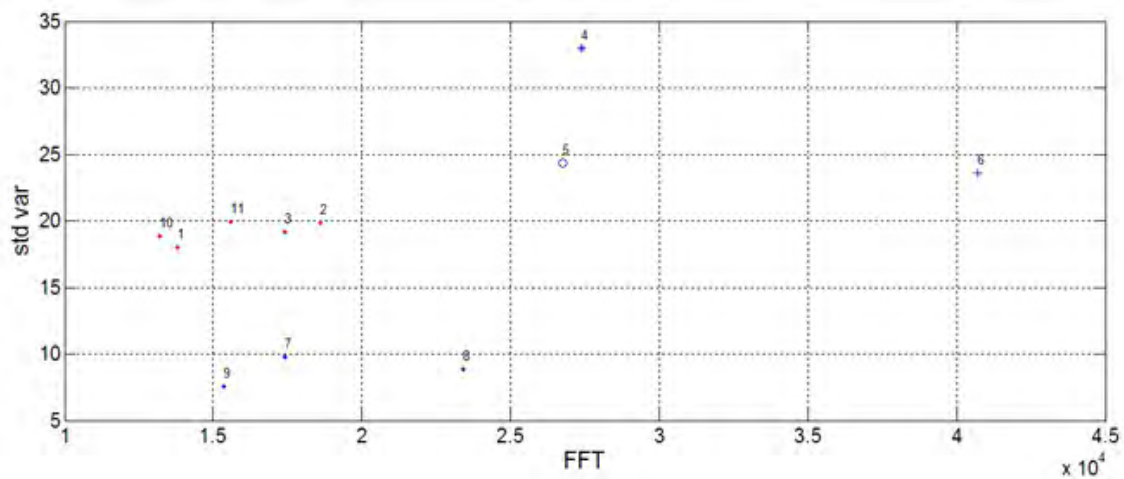


Figure 18. Clustering of the joint damage detection experiment

On the right hand side of Figure 17, the different intensity histograms are shown. No.1, 4 and 7 are shown below. Area No.4 is where a large defect at the joint is shown and clearly shows a widened distribution in the intensity histogram and a sharp contrast in the 2D spectral image. This is a clear contrast to areas 1 and 7 which represent the undamaged portions of the bridge deck and joint area.



Figure 19. The bend beam used for experiment

Figure 19 shows the LiDAR scan of a reinforced concrete beam with bending cracks at the lower portion of the beam. Several portions of the beam were isolated into cells for analysis, which are shown in Figure 20. The k-values for each portion are plotted in Figure 21 to help differentiate the damaged portions. As shown, the larger groups are good areas, and the portions clustered near the bottom of the graph are indication of beam cracks.

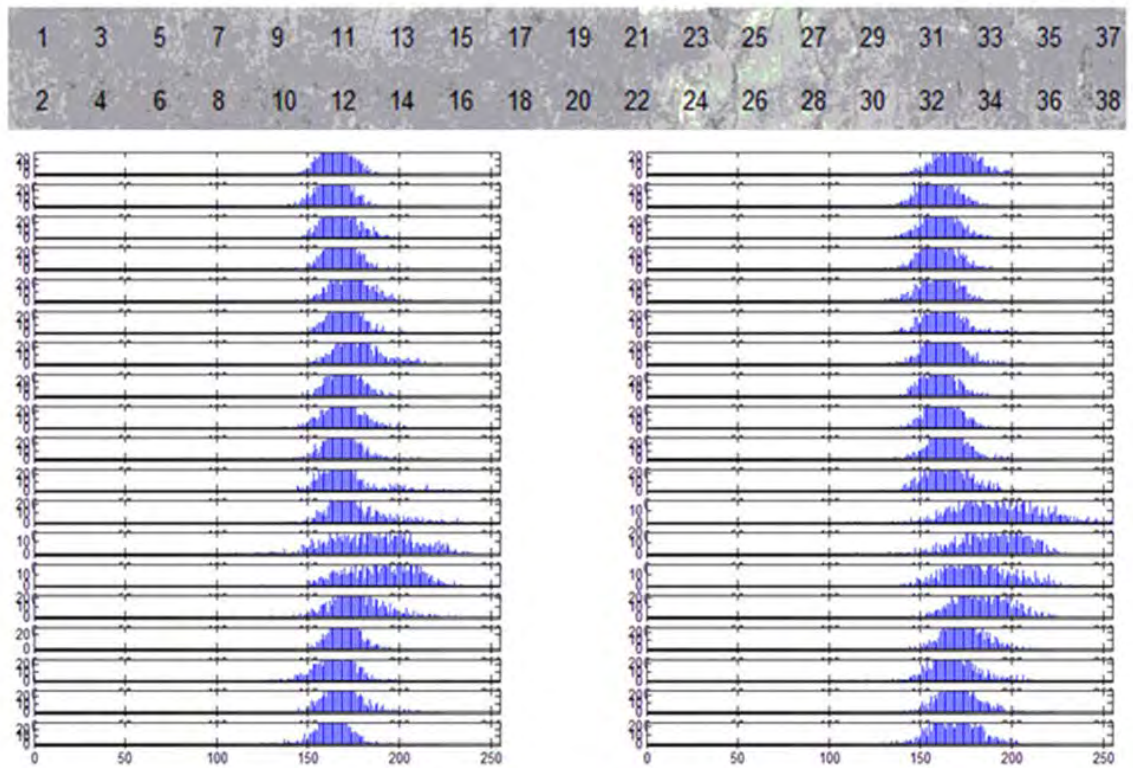


Figure 20. Intensity histogram of the divided beam cells

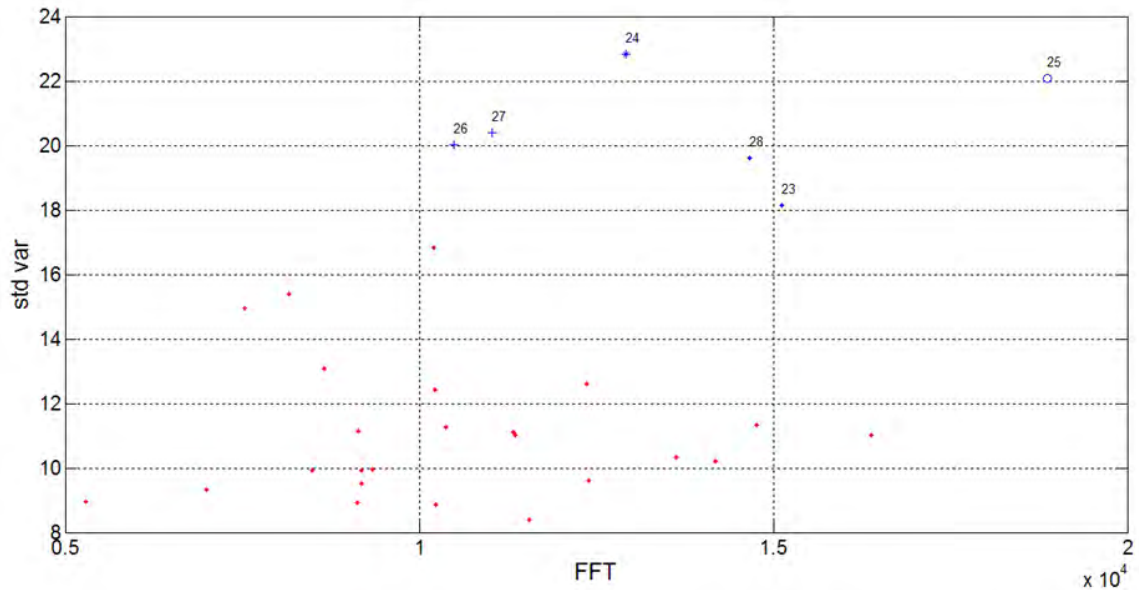


Figure 21. Groups based on characteristic values Figure

3.3.4 Summary

The previous developed LiDAR data defective detection methods mainly deal with the spatial information and require the object surface is flat. In this chapter, an attempt is made to apply reflectivity measurements of LiDAR data to explore the possibility of enhanced damage recognition automation for bridge inspection. The most outstanding breakthrough of the new approach is that it can be used to inspect any smooth surfaces. The automatic bridge defect identification program is presented in detail. Two examples of defect detection are also presented. The result indicates that it's effective and reliable to identify bridge defects using this reflectivity based method. The study presented in this chapter mainly targets at the qualitative side of the defect detection, while the next step is to integrate this new approach along with previous quantitative approach into an effective defect detection algorithm.

3.4 US DOT BRIDGE SCAN REPORT

This project offers an opportunity to investigate the possibility of remote sensing technologies in bridge inspection at a national scale. During the entire project phase, a total of 88 bridges were studied using LiDAR scan in North Carolina, Alabama, Florida, New York, and California. Plenty of bridge data has been collected.

From the total 88 highway bridges selected in this research: 47 of them have been inspected for damage, 16 of them have been measured for clearance, and 25 of them have been conducted both.

3.4.1 The Capability of LiDAR Bridge Inspection

Figure 22 shows a large scale mass loss under the bridge girder (Bridge 42300, IA). Due to the widespread damaged area, the algorithm which focuses on analysis of a single damage area cannot be used in this case. However, the damage portion could be clearly visualized in the 3D reconstruction (See Figure 23).



Figure 22. The large scale mass loss in Bridge 42300

The current damage detection algorithms focus more on local defects rather than large scale or even global defects as in this case. The identification of large defect zones is feasible by including the pattern of the surface and its variation in the future study.

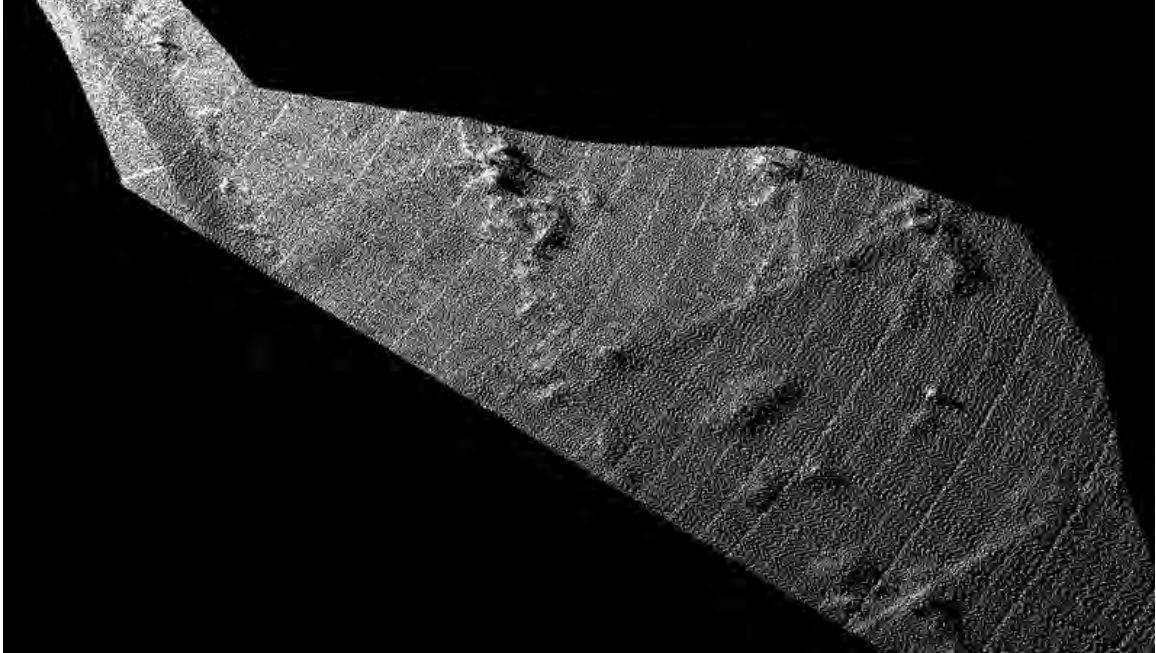


Figure 23. The LiDAR reconstruction of the damage area

The quantification of local damage in bridges is the most advanced feature of LiDAR inspection. The defective areas such like mass loss of material, pot holes, or even small damages due to concrete pop-out from corroded rebars could be easily quantified by employing this new technology.

Figure 24 shows an example of rebar exposure damage quantification of bridge 000941 in Alabama. From the manual measurement in the first step, the length of this damage is 0.073m and the width is even smaller. The algorithm has identified this defect successfully, and has been marked in the 3D inspection result demonstration. By utilizing this LiDAR inspection, it would be a great improvement in efficiency and accuracy when bridge inspectors are trying to quantify damages like this.

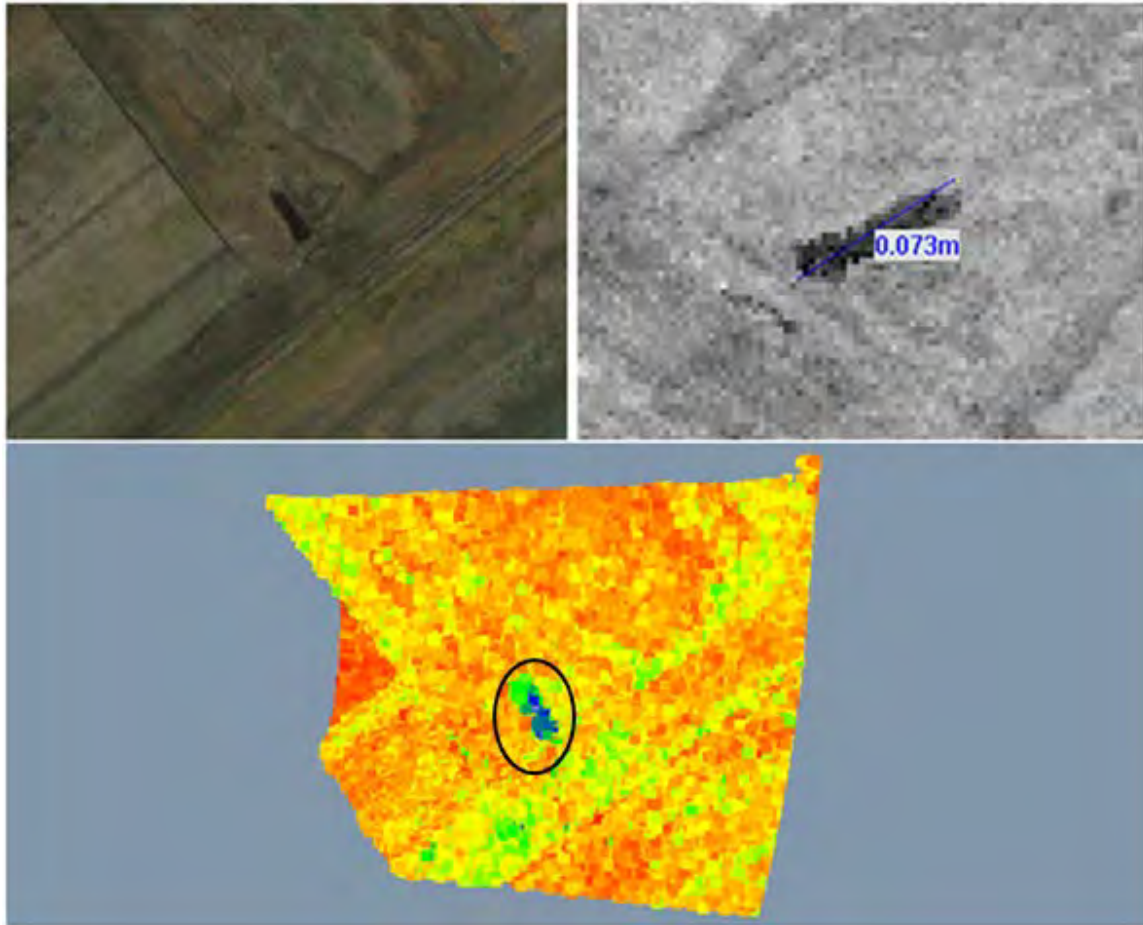


Figure 24. Rebar exposure damage can actually quantify with LiDAR inspection

This particular case is a good example that explains LiDAR is capable for some minor defect inspection in bridges. The limitation of using LiDAR for damage quantification is when the damages are too small or do not reflect enough laser points, the inspection algorithm will not get the result.

In Figure 25, the damage is also caused due to concrete pop-out from corroded rebars and the defect portion could be recognized in the LiDAR scan visually. The algorithm is failed to identify this damage due to low pixel resolution. However, general measurement of the damage size can be determined using LiDAR scan. Under this situation, it's impossible to quantify the damage using the current program while it still could be estimated by determining the edge of this defect if including image processing.

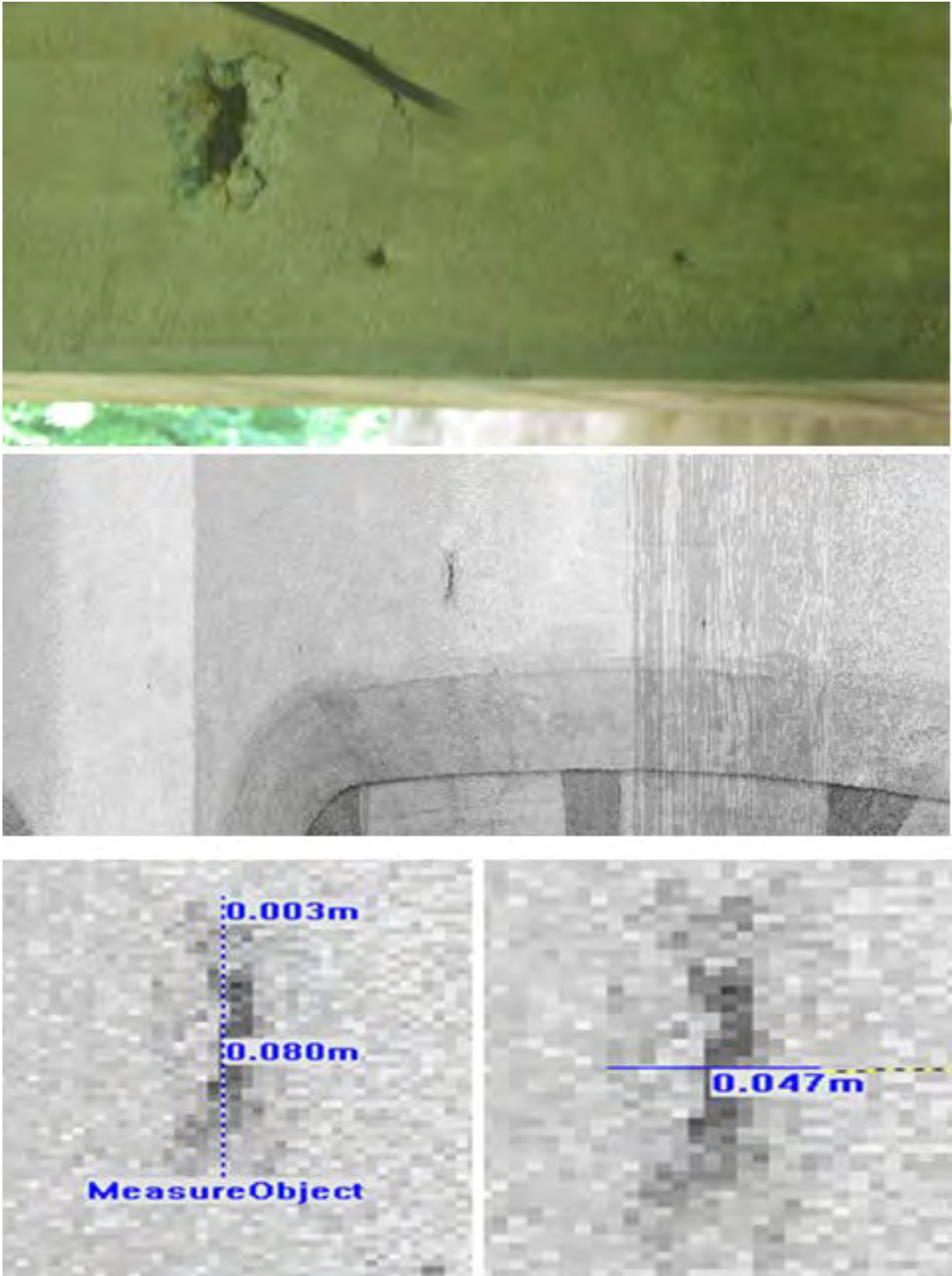


Figure 25. Rebar exposure damage cannot be quantified with LiDAR inspection

3.4.2 Noises in LiDAR Scan

There are some factors that might prevent the LiDAR getting clear field data. Passing traffic effect is one of the most common issues when scanning a bridge with heavy traffic, and the vehicles would leave scatters of lines in the scan. The effect creates trouble in the data analysis by distorting the scanned image. In both damage detection and clearance measurement, this issue could lead to error.

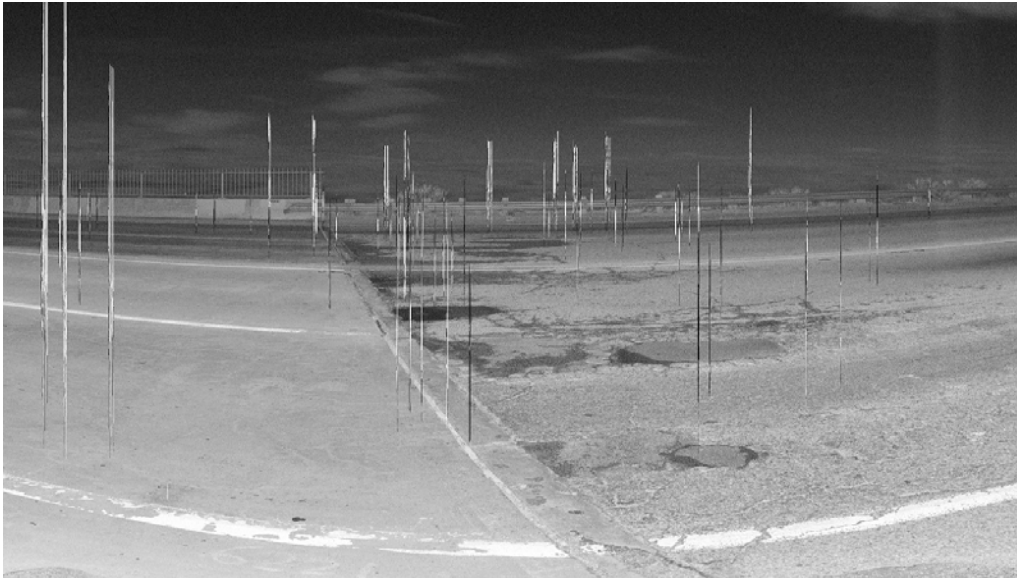


Figure 26. A LiDAR scan for road surface affected by passing traffic.

3.4.3 Specific LiDAR Applications

(1) Crack Measurement

The LiDAR scan could be used to measure cracks in bridges. Figure 27 shows the measurement of a longitudinal crack and a crack with complex path.

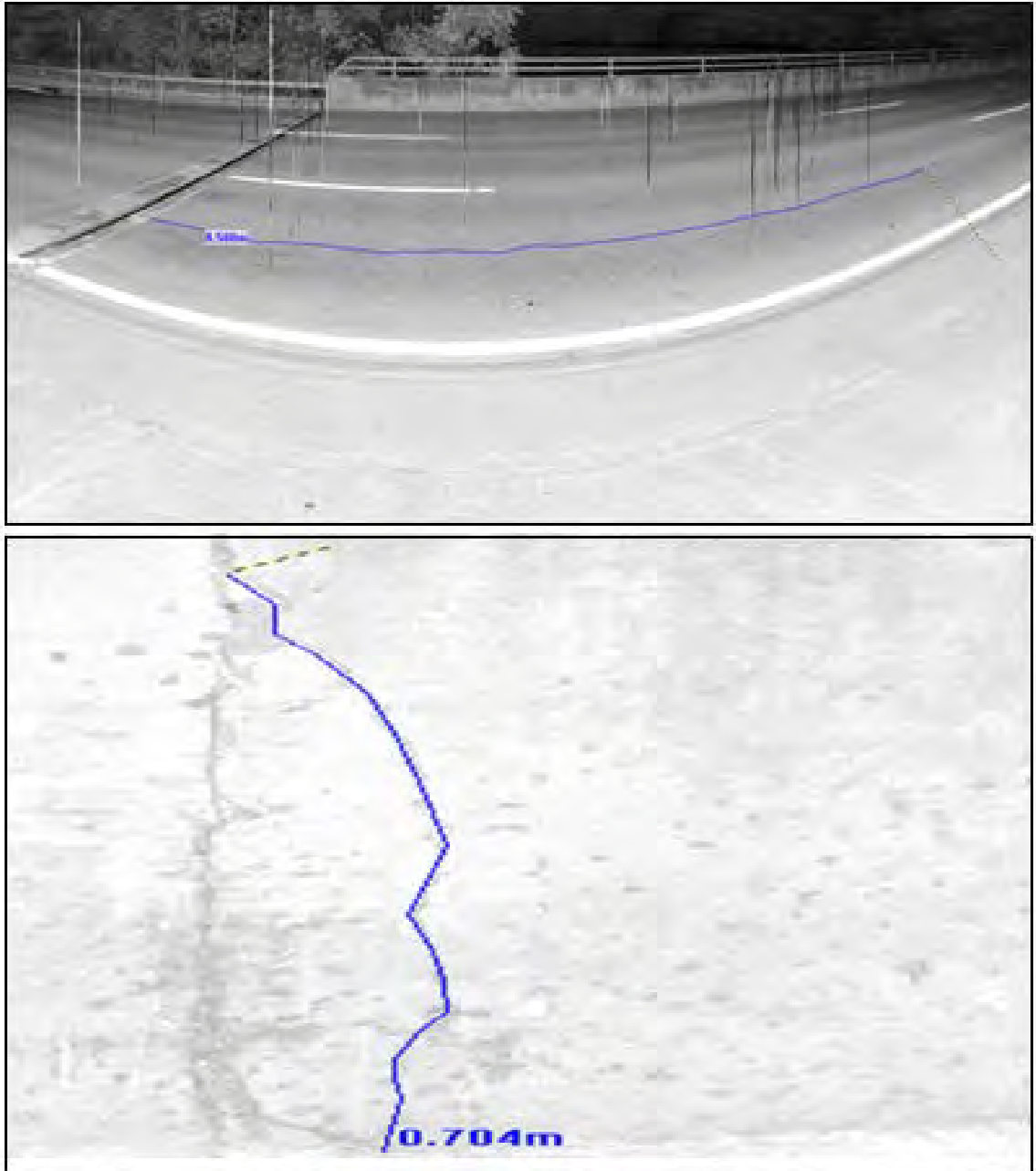


Figure 27. Crack measurement using LiDAR data

(2) Mass Loss of Material Quantification

Mass loss of material quantification is the primary application in LiDAR bridge inspection. Figure 28 shows the inspection result of a mass loss due to push out from corroded rebar. Figure 29 show the quantification of a pot hole on bridge surface. Both of them are visualized in 3D. Figure 30 the quantification of wall damage with backfill loss. Figure 31 shows a case where damage with complex geometry can be quantified.

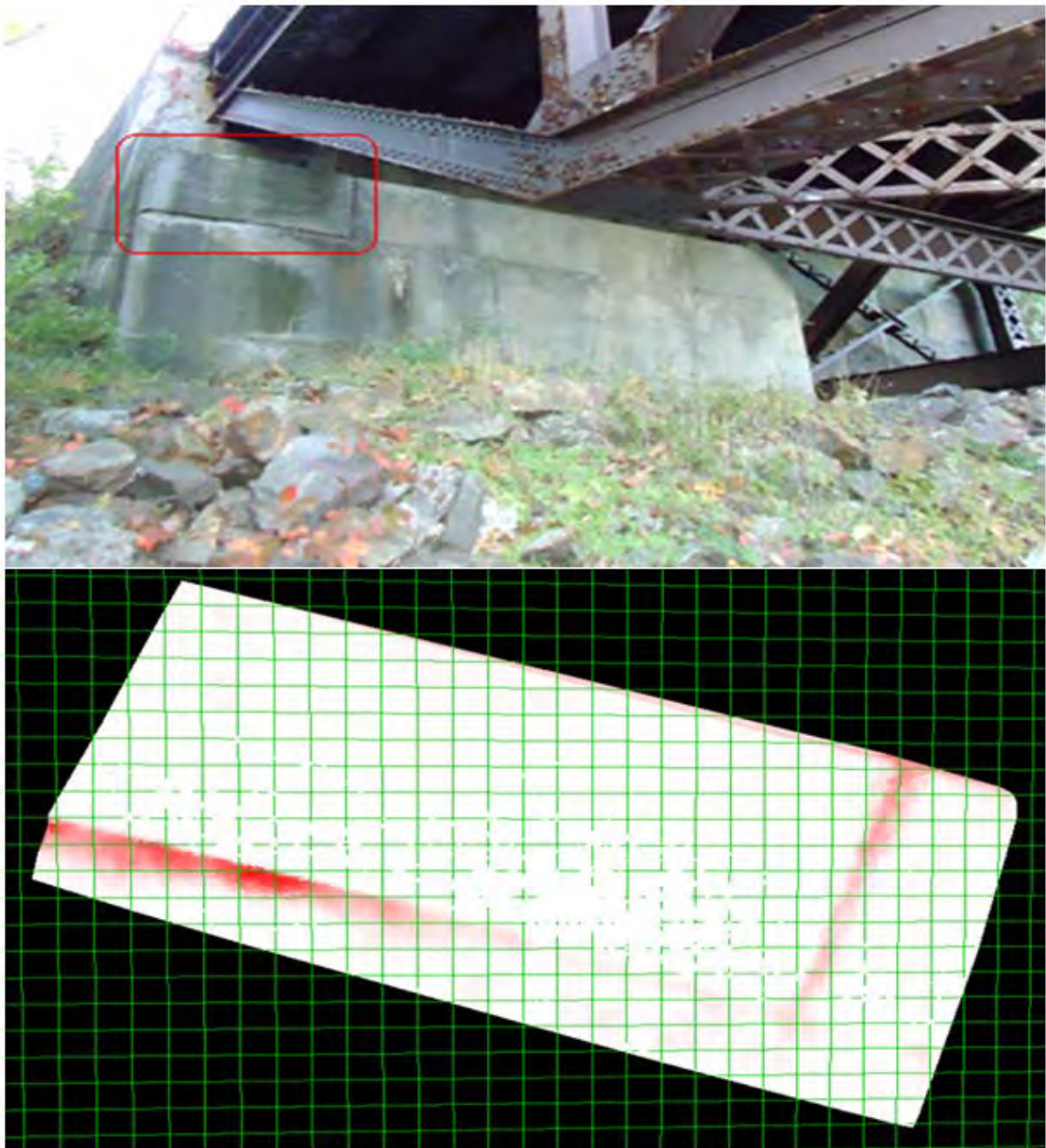


Figure 28. Mass loss due to push out from corroded rebar

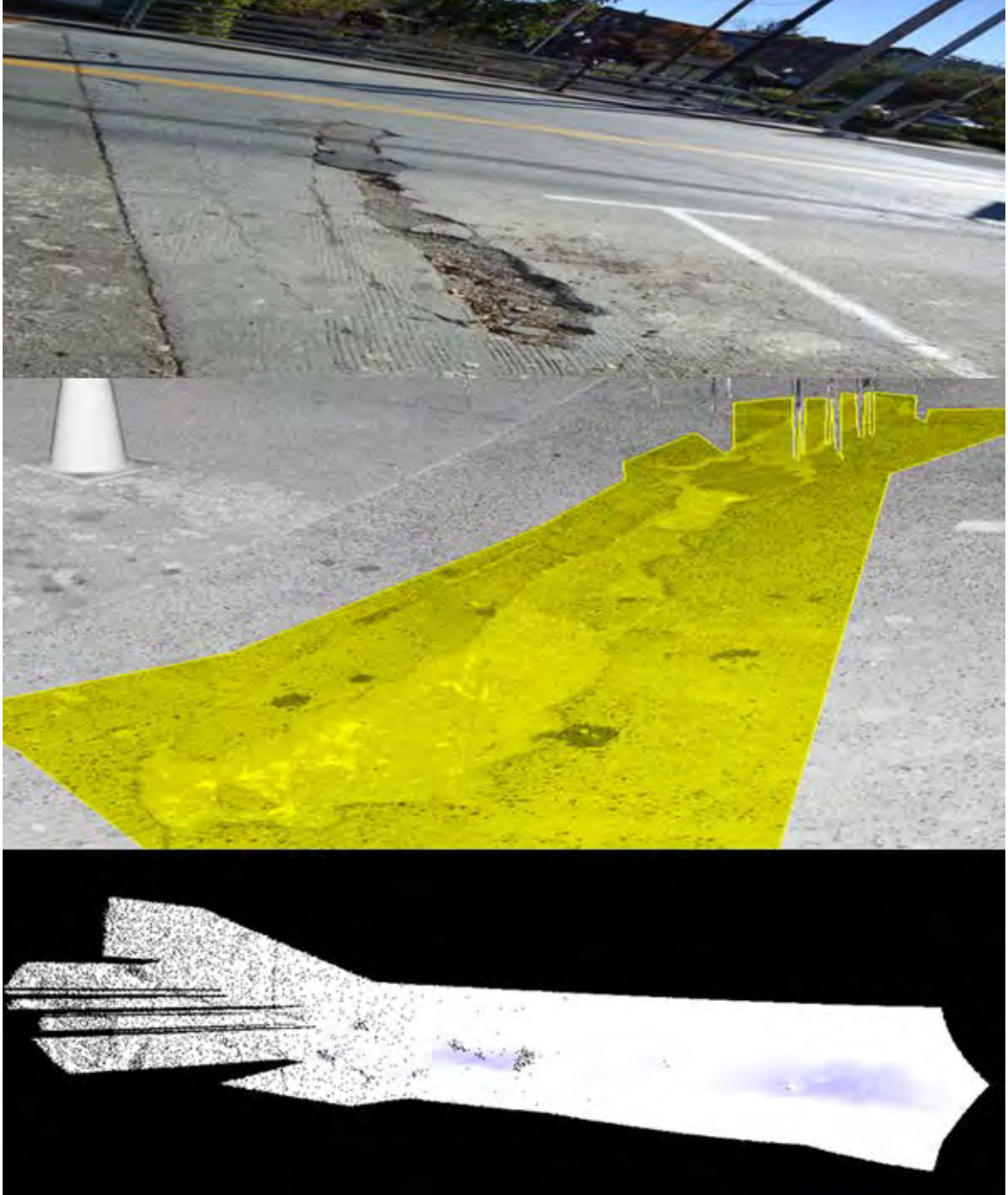


Figure 29. Pot hole quantification using LiDAR data

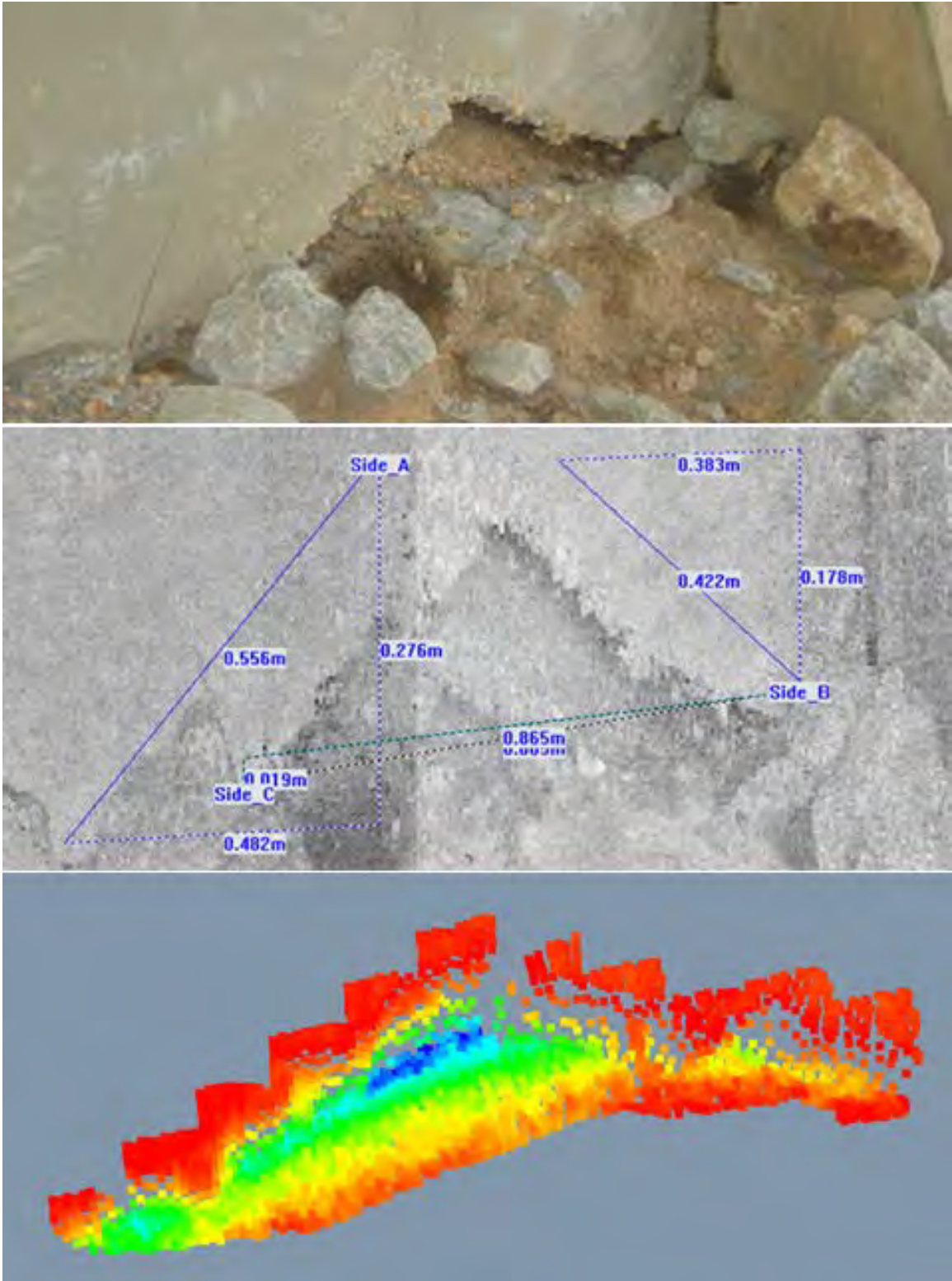


Figure 30. Wall damage with backfill loss

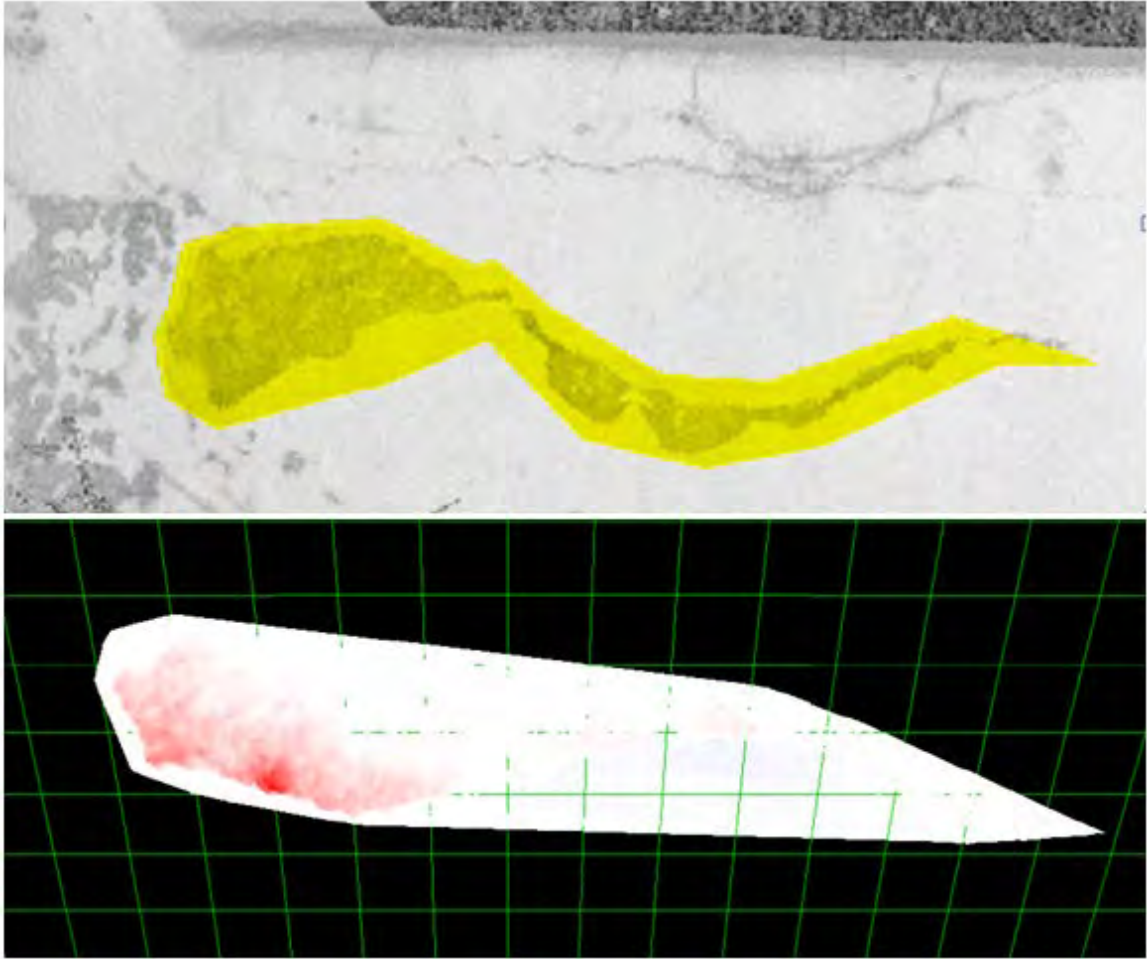


Figure 31. Damage with complex geometry

(3) LiDAR Inspection for Potential Damage

Finally, Figure 32 shows the quantification of a potential damage area where discolored section indicates future pop-out area.

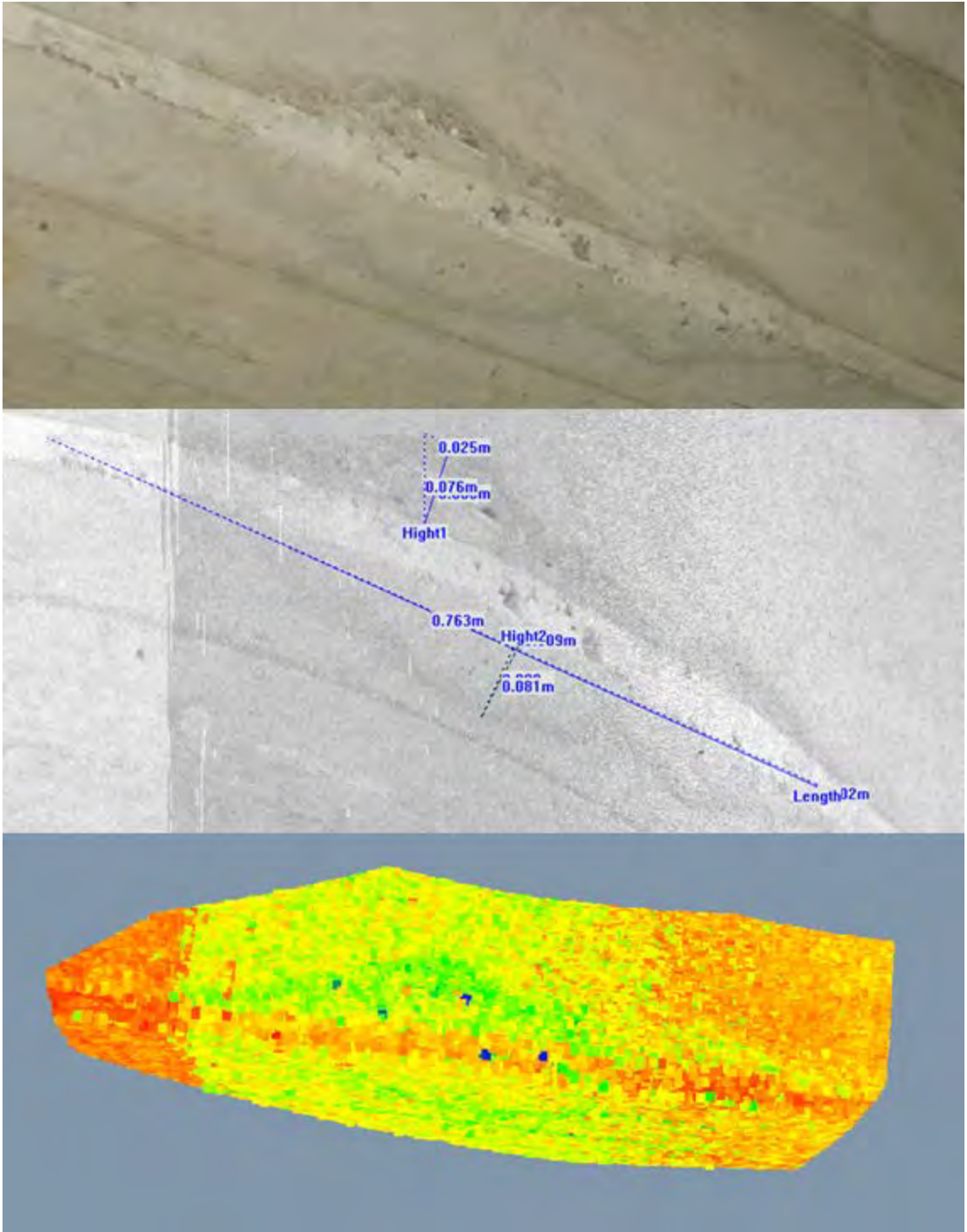


Figure 32. Potential damage area actually being quantified (before mass loss)

3.5 SUMMARY AND CONCLUSIONS

Terrestrial LIDAR is one of the remote sensing tools that have been reported in bridge evaluation. Most of the early measurement algorithms mentioned in this report are developed based on the spatial information contained from the LIDAR data. By populating a surface with numerous laser points, LiDAR generates point cloud data, which is essentially 3D geometric information that can be used to quantify surface anomalies. Information such as how much concrete mass losses and how quickly the deterioration process can be useful for bridge management decision making or life cycle analysis of bridges.

The study conducted in this report verified the potential of applying LiDAR data in bridge damage inspection, and further investigation approaches to improve analytical results :

- (1) For LiDAR setup, the scan angle can influence scan result and cause error in area and volume calculation. The outcome may be more than 20% off from the actual damage.
- (2) For the damage detection algorithm, a new approach to identify and quantify the investigation areas was developed and presented to compare the detection results with the previous algorithm. The MSE&T method is slightly better than the method (<5%).
- (3) For the LiDAR scan data itself, the reflectivity was used as a new feature in damage detection combined with existing image processing.

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APPENDIX A: BRIDGE SCAN DATA

NORTH CAROLINA

1. 590038

LiDAR Scan



Figure-A1

3D Reconstruction

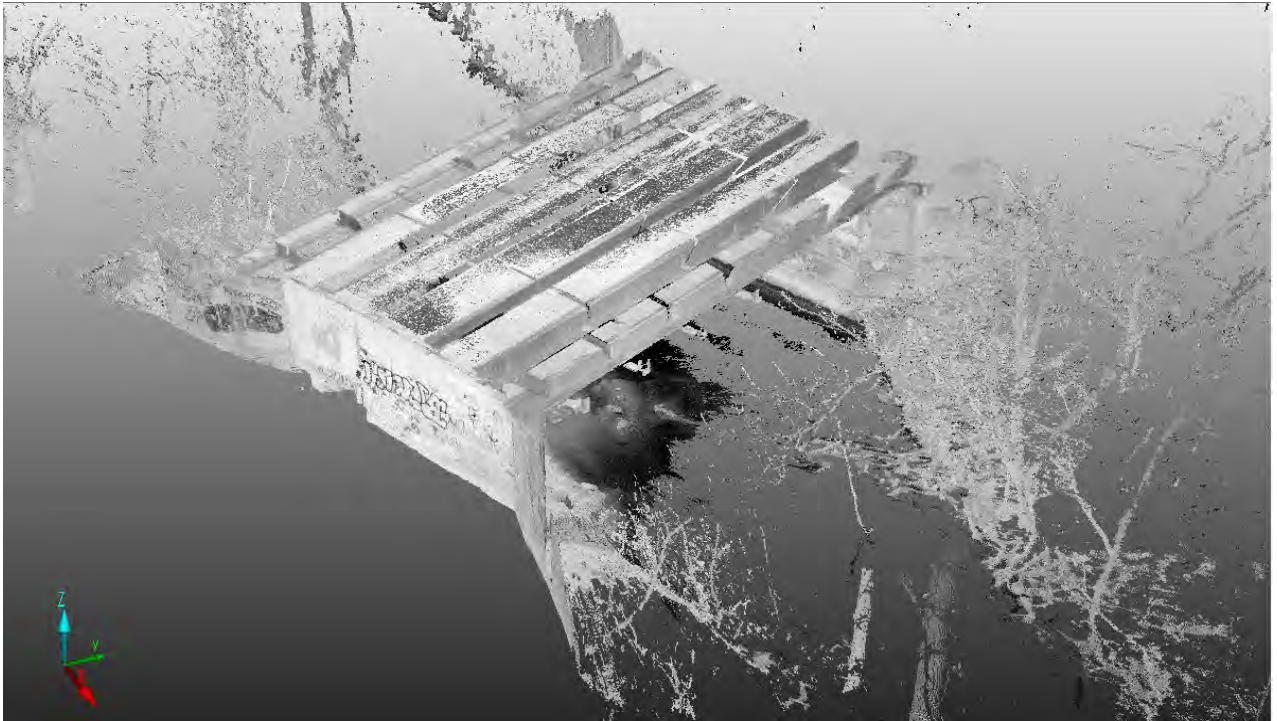


Figure-A2

Integrated Remote Sensing and Visualization

Phase Two, Volume Three: Advanced Consideration in LiDAR Technology

2. 590049

LiDAR Scan

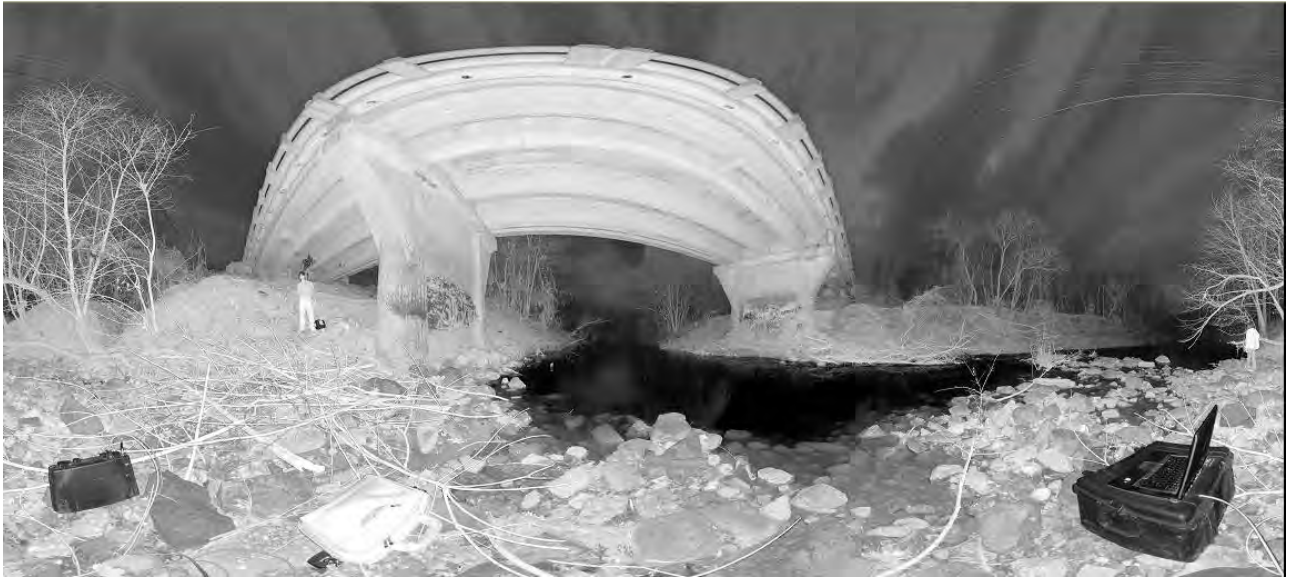


Figure-A3

3D Reconstruction



Figure-A4

3. 590059

LiDAR Scan



Figure-A5

3D Reconstruction



Figure-A6

4. 590084

LiDAR Scan



Figure-A7

3D Reconstruction



Figure-A8

5. 590108

LiDAR Scan

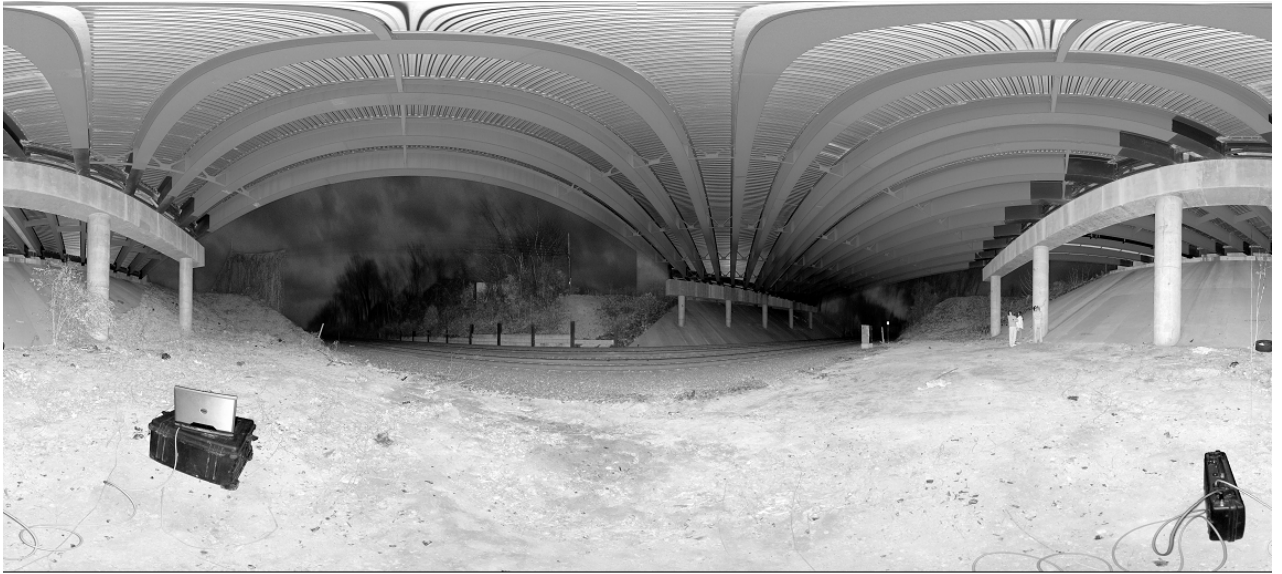


Figure-A9

3D Reconstruction

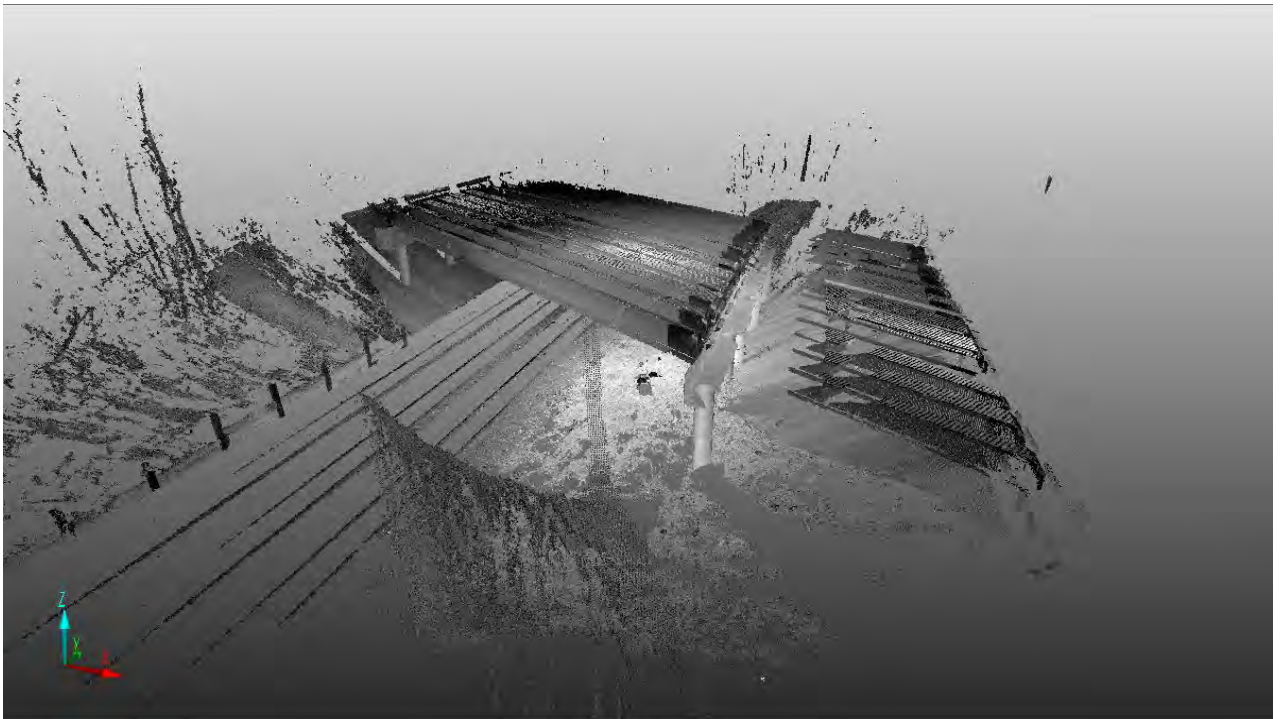


Figure-A10

6. 590140

LiDAR Scan



Figure-A11

3D Reconstruction

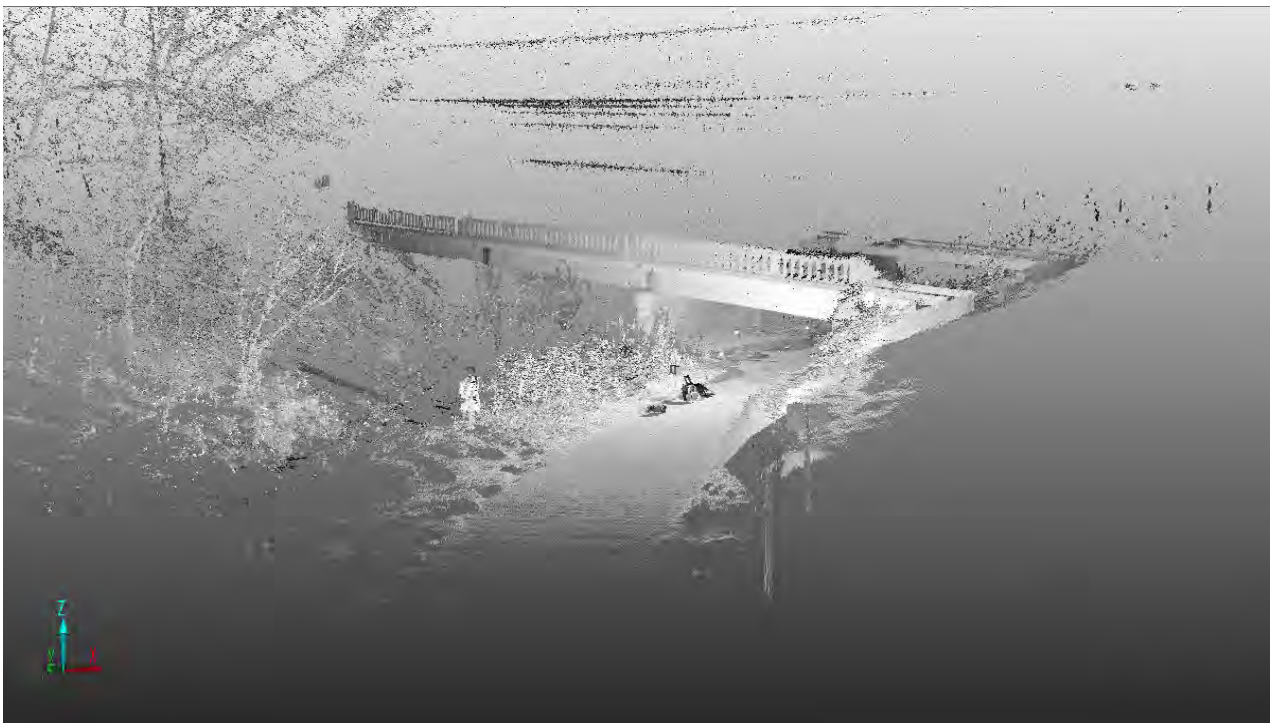


Figure-A12

7. 590147

LiDAR Scan



Figure-A13

3D Reconstruction



Figure-A14

8. 590161

LiDAR Scan



Figure-A15

3D Reconstruction

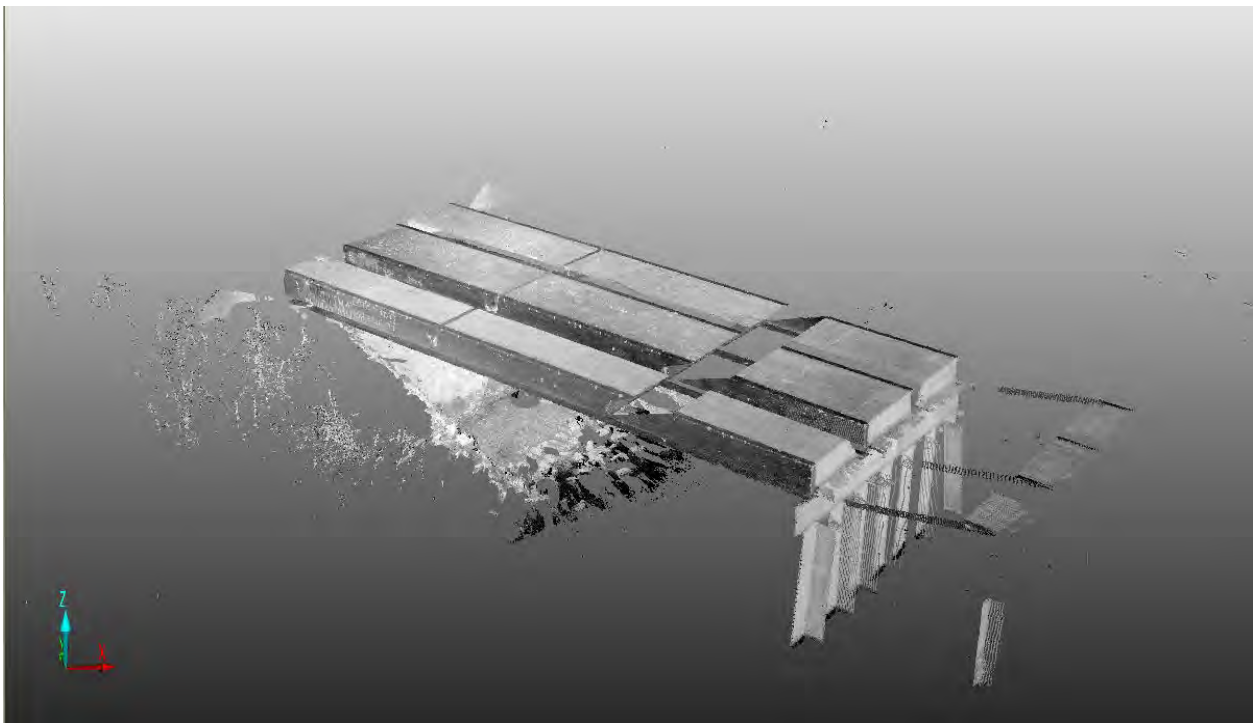


Figure-A16

9. 590165

LiDAR Scan



Figure-A17

3D Reconstruction



Figure-A18

10. 590176

LiDAR Scan



Figure-A19

3D Reconstruction



Figure-A20

11. 590177

LiDAR Scan



Figure-A21

3D Reconstruction



Figure-A22

12. 590179

LiDAR Scan



Figure-A23

3D Reconstruction



Figure-A24

13. 590239

LiDAR Scan



Figure-A24

3D Reconstruction



Figure-A25

14. 590255

LiDAR Scan



Figure-A26

3D Reconstruction



Figure-A27

15. 590298

LiDAR Scan



Figure-A28

3D Reconstruction



Figure-A29

16. 590379

LiDAR Scan



Figure-A30

3D Reconstruction

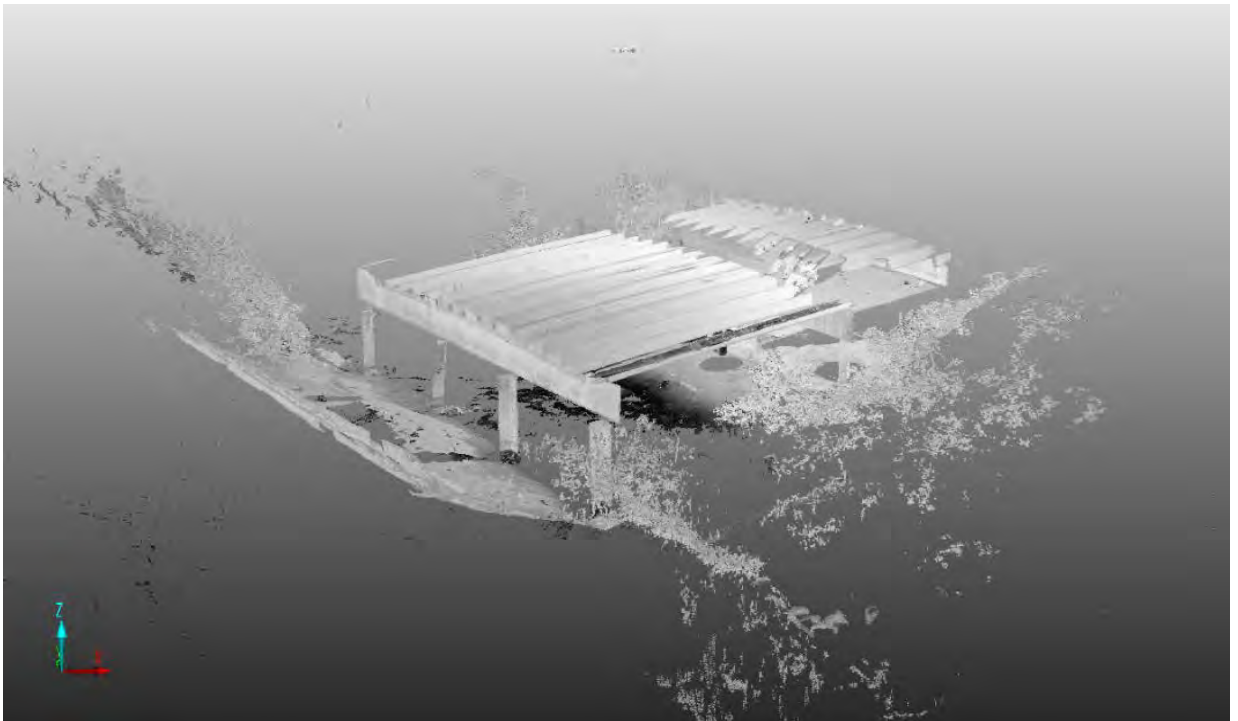


Figure-A31

17. 590511

LiDAR Scan



Figure-A32

3D Reconstruction



Figure-A33

18. 590700

LiDAR Scan

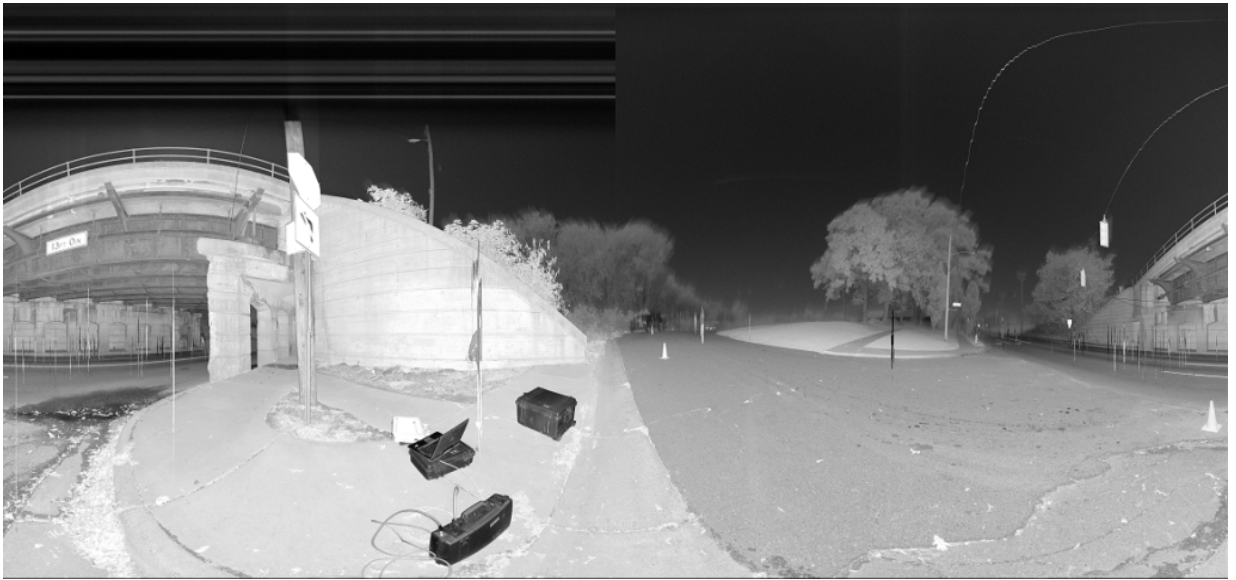


Figure-A34

3D Reconstruction



Figure-A35

19. 590702

LiDAR Scan



Figure-A36

3D Reconstruction



Figure-A37

20. 590704

LiDAR Scan



Figure-A38

3D Reconstruction



Figure-A39

21. Catawba34

LiDAR Scan



Figure-A40

3D Reconstruction

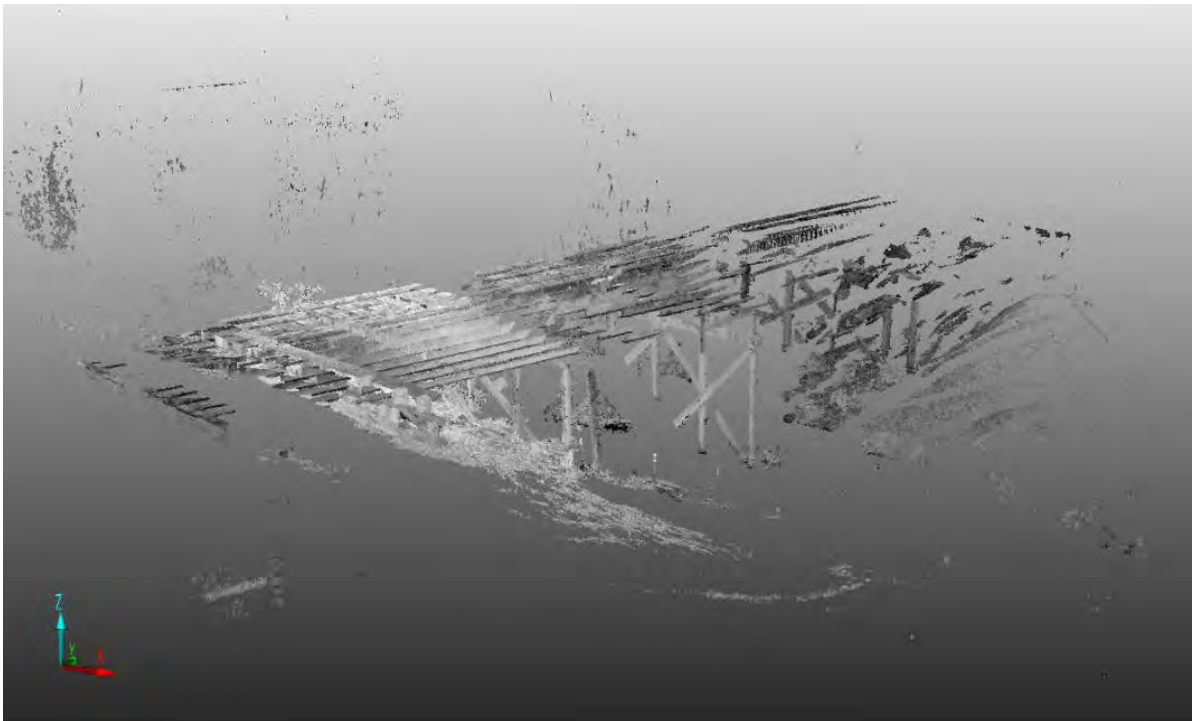


Figure-A41

22. Catawba91

LiDAR Scan



Figure-A42

3D Reconstruction



Figure-A43

23. Colony Bridge

LiDAR Scan

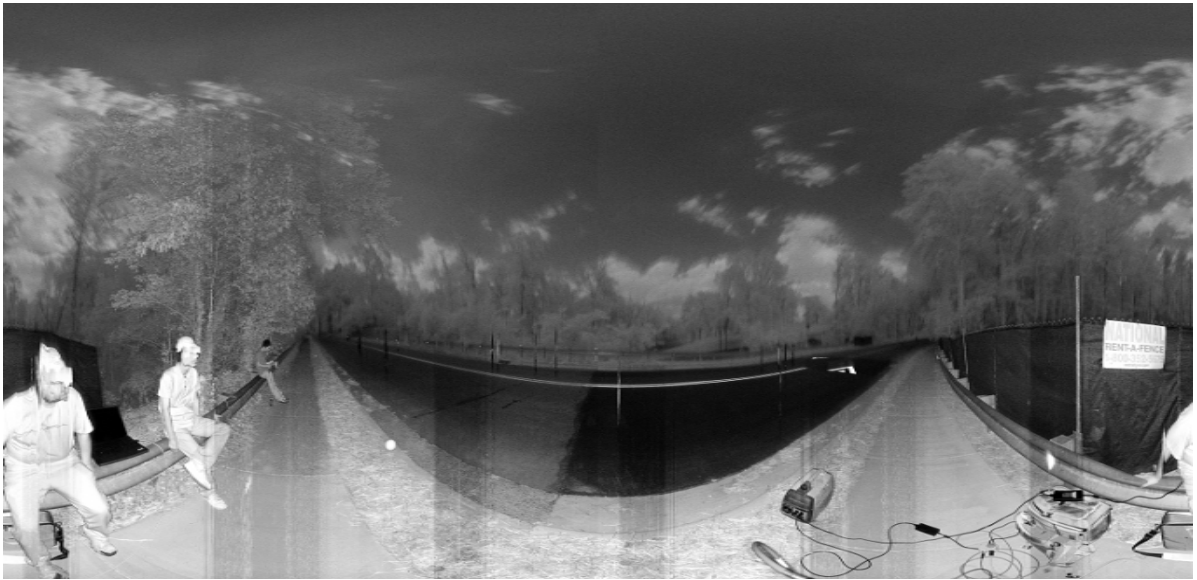


Figure-A44

3D Reconstruction



Figure-A45

24. CowansFord

LiDAR Scan



Figure-A46

3D Reconstruction



Figure-A47

25. Harris Bridge

LiDAR Scan



Figure-A48

3D Reconstruction



Figure-A49

26. I40

LiDAR Scan



Figure-A50

3D Reconstruction



Figure-A51

27. Lincoln266

LiDAR Scan



Figure-A52

3D Reconstruction

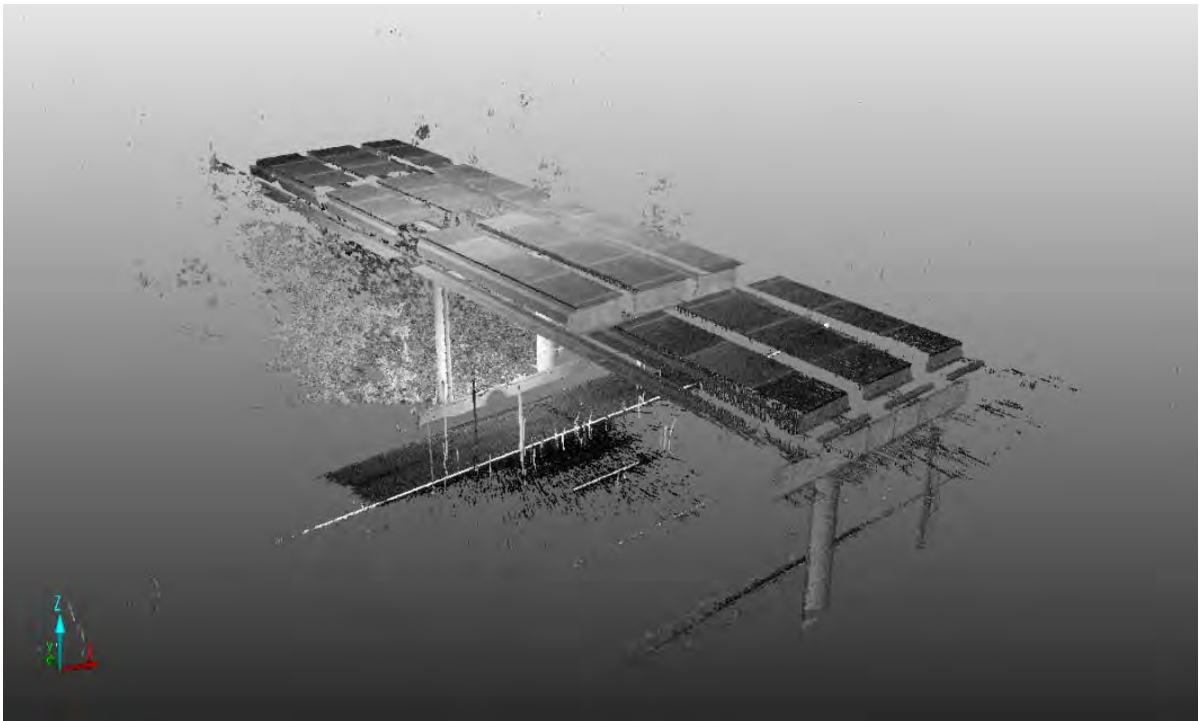


Figure-A53

28. Mallard Creek Bridge

LiDAR Scan (1)



Figure-A54

3D Reconstruction (1)



Figure-A55

Mallard Creek Bridge

LiDAR Scan (2)



Figure-A56

3D Reconstruction (2)



Figure-A57

Mallard Creek Bridge

LiDAR Scan (3)



Figure-A58

3D Reconstruction (3)



Figure-A59

29. Tryon Bridge

LiDAR Scan (1)



Figure-A60

3D Reconstruction (1)



Figure-A61

30. Uptown Steel Bridge

LiDAR Scan (2)



Figure-A62

3D Reconstruction (2)



Figure-A63

ALABAMA

1. 000198

LiDAR Scan



Figure-A64

3D Reconstruction



Figure-A65

2. 000933

LiDAR Scan

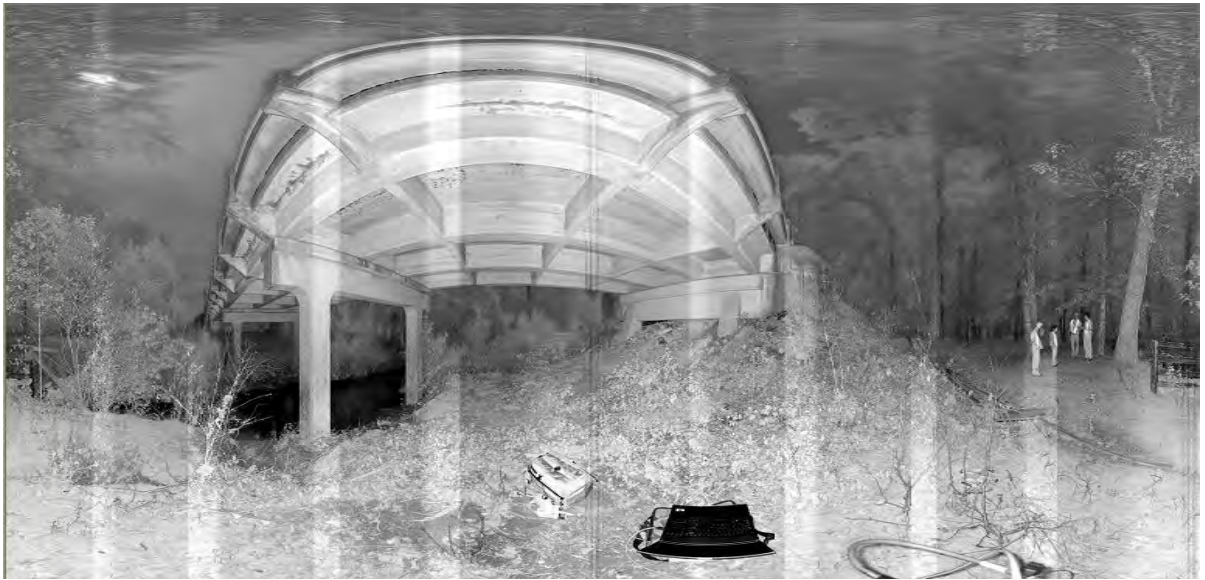


Figure-A66

3D Reconstruction



Figure-A67

3. 000935

LiDAR Scan



Figure-A68

3D Reconstruction



Figure-A69

4. 000941

LiDAR Scan



Figure-A70

3D Reconstruction



Figure-A71

5. 002380

LiDAR Scan (1)



Figure-A72

3D Reconstruction

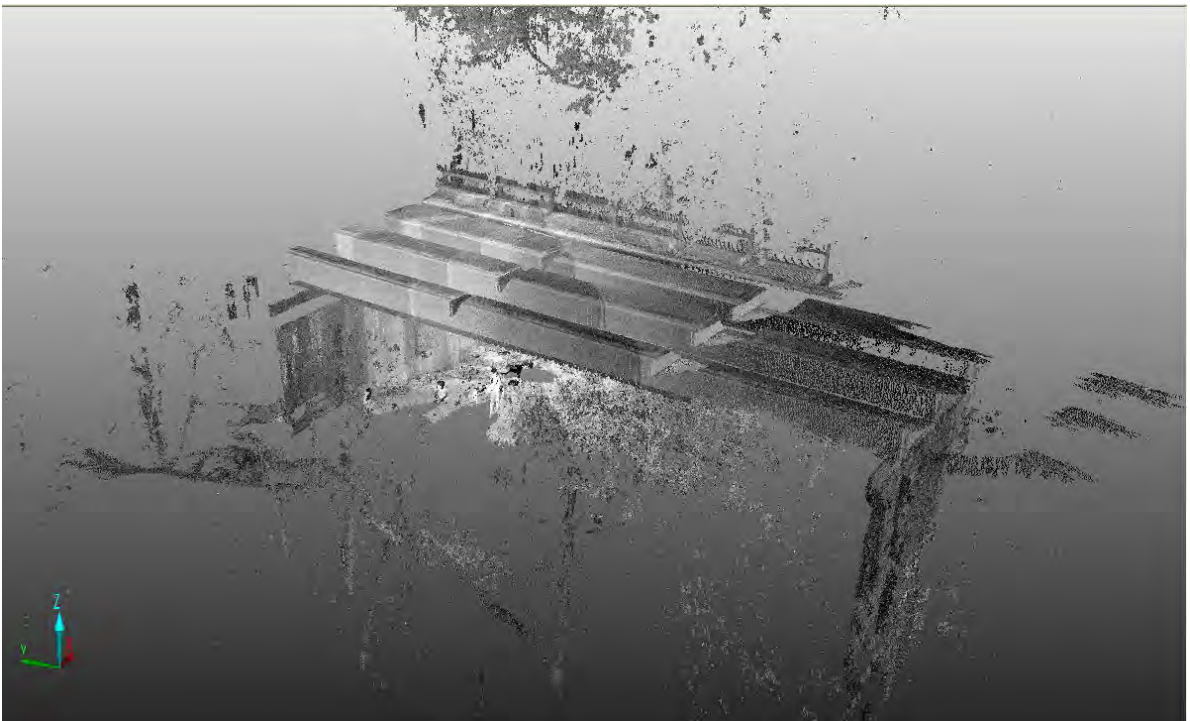


Figure-A73

002380

LiDAR Scan (2)



Figure-A74

3D Reconstruction



Figure-A75

6. 003267

LiDAR Scan



Figure-A76

3D Reconstruction



Figure-A77

7. 005480

LiDAR Scan



Figure-A78

3D Reconstruction

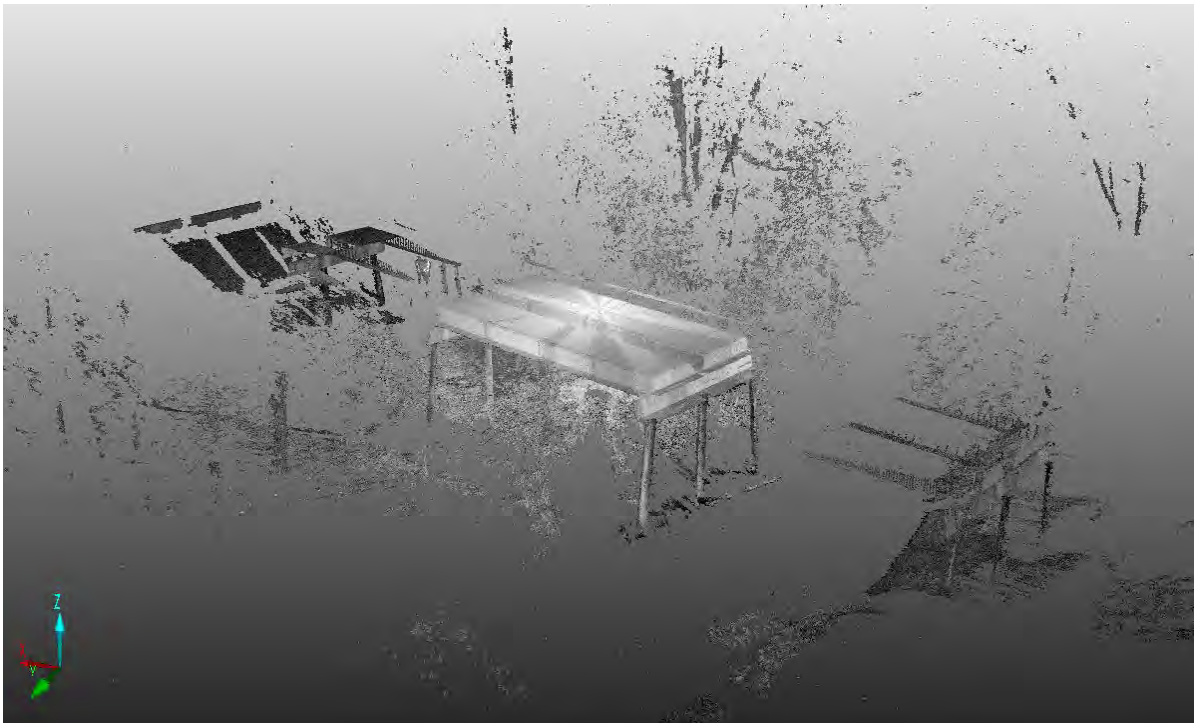


Figure-A79

8. 005369

LiDAR Scan



Figure-A80

3D Reconstruction



Figure-A81

9. 007390

LiDAR Scan



Figure-A88

3D Reconstruction



Figure-A89

10. 010357

LiDAR Scan



Figure-A84

3D Reconstruction



Figure-A85

11. 006952

LiDAR Scan



Figure-A86

3D Reconstruction



Figure-A87

12. 011015

LiDAR Scan

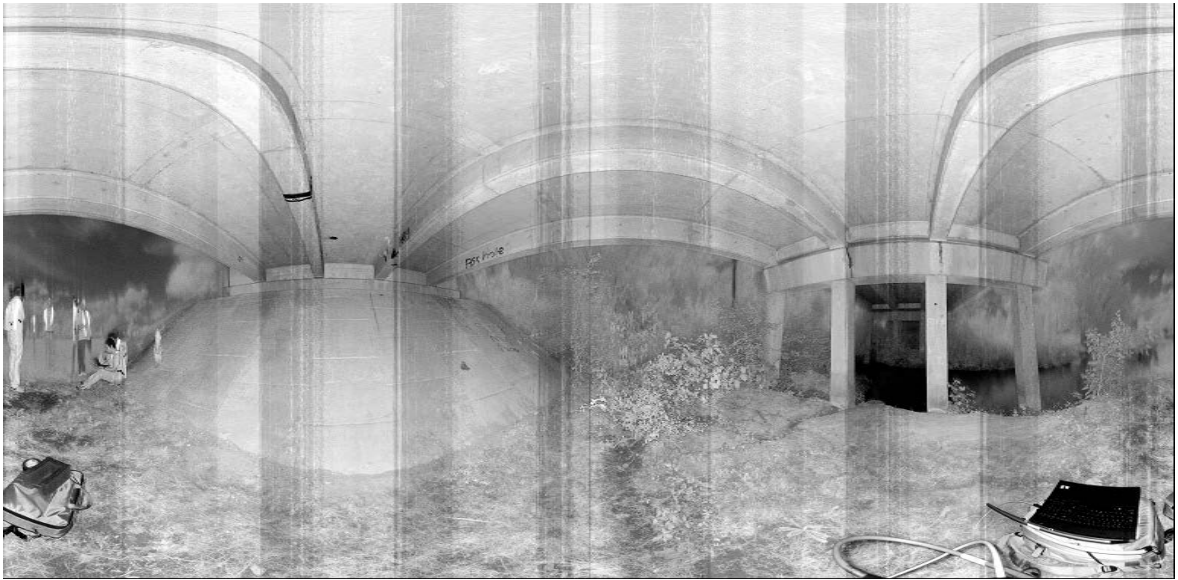


Figure-A90

3D Reconstruction



Figure-A91

FLORIDA

1. 924038

LiDAR Scan (1)

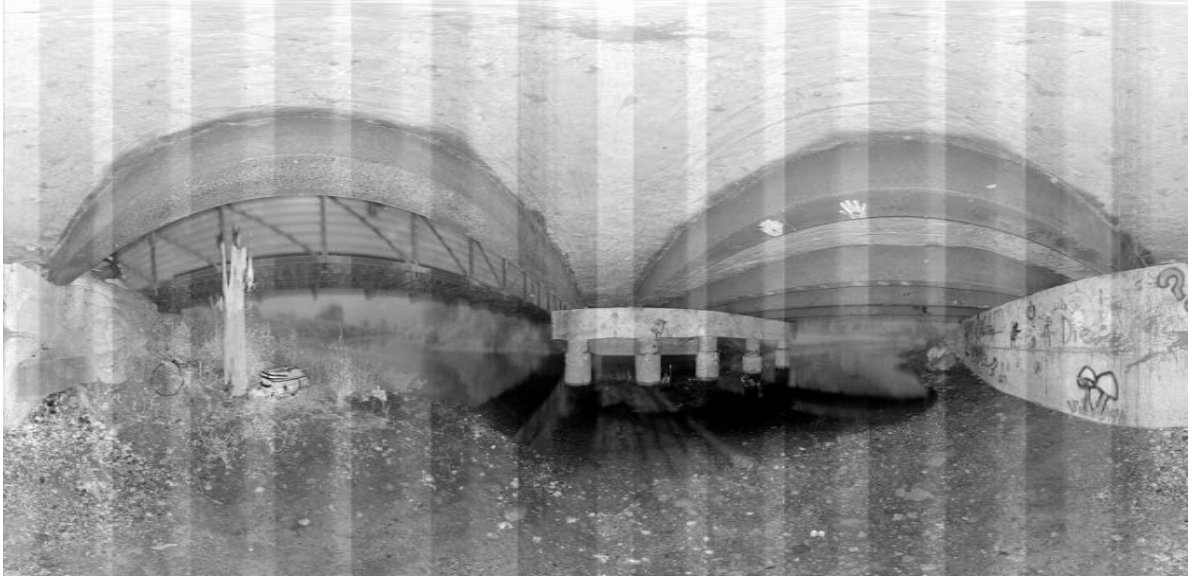


Figure-A92

3D Reconstruction (1)



Figure-A93

924038

LiDAR Scan (2)



Figure-A94

3D Reconstruction (2)



Figure-A95

2. 924049

LiDAR Scan

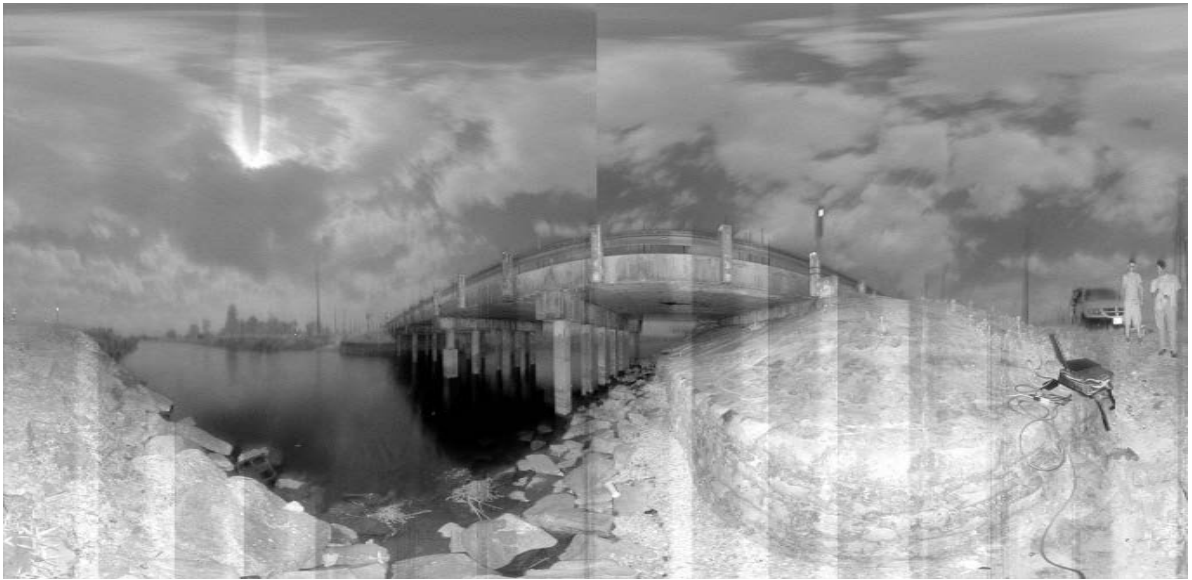


Figure-A96

3D Reconstruction



Figure-A97

3. 924150

LiDAR Scan (1)

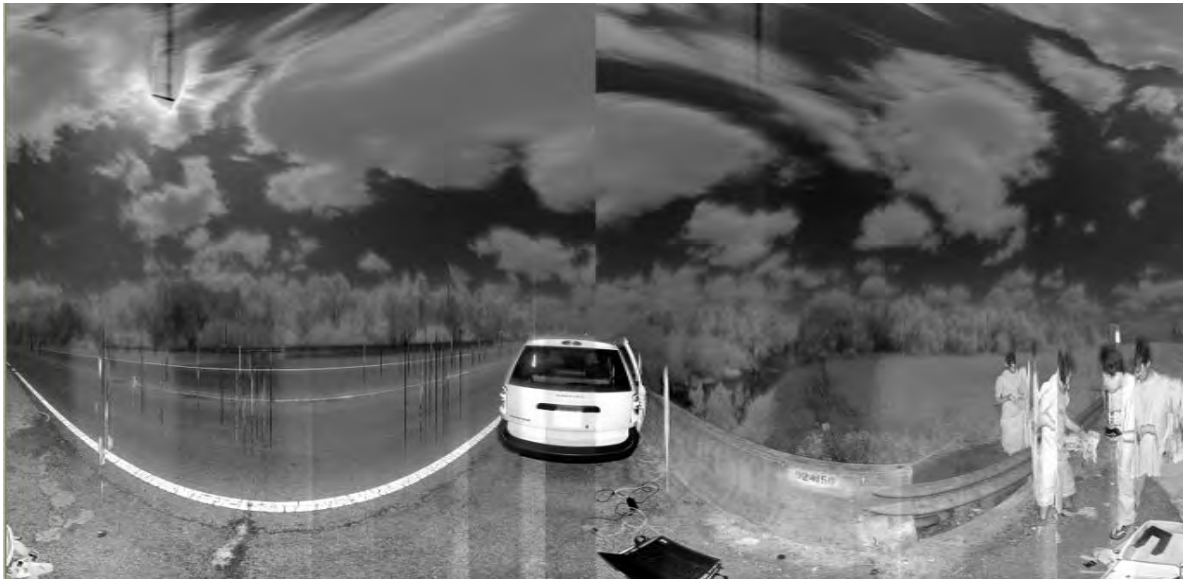


Figure-A98

3D Reconstruction



Figure-A99

924150

LiDAR Scan (2)



Figure-A100

3D Reconstruction

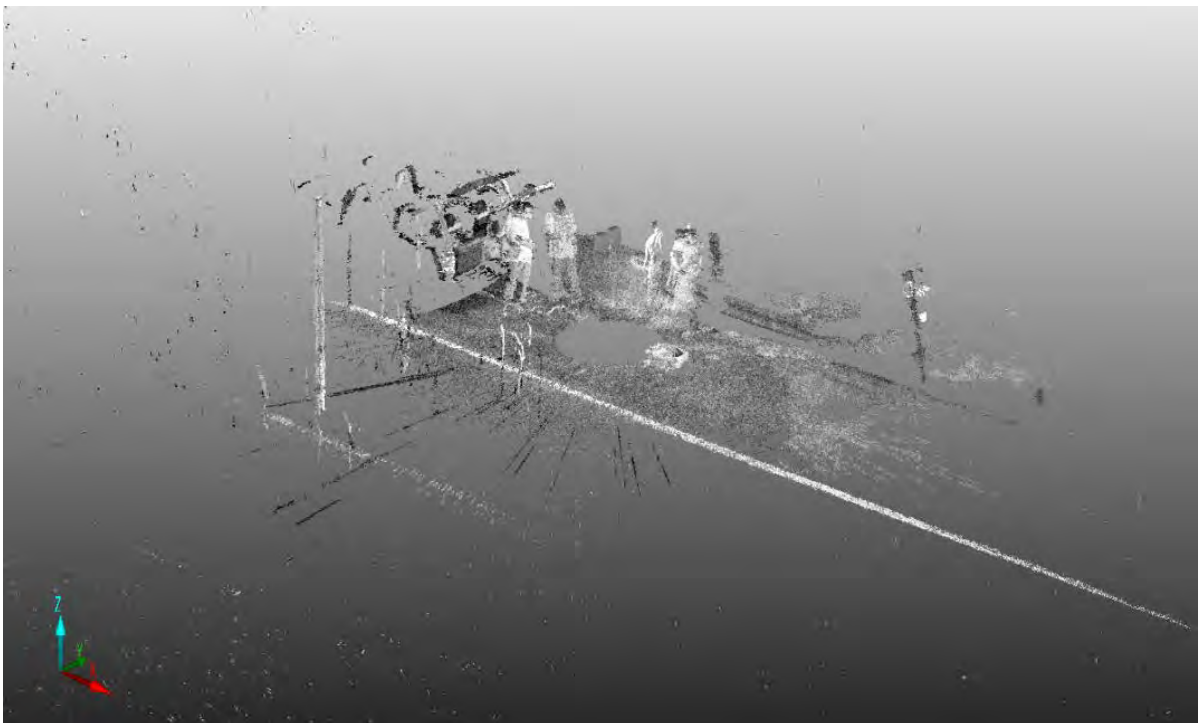


Figure-A101

924150

LiDAR Scan (3)

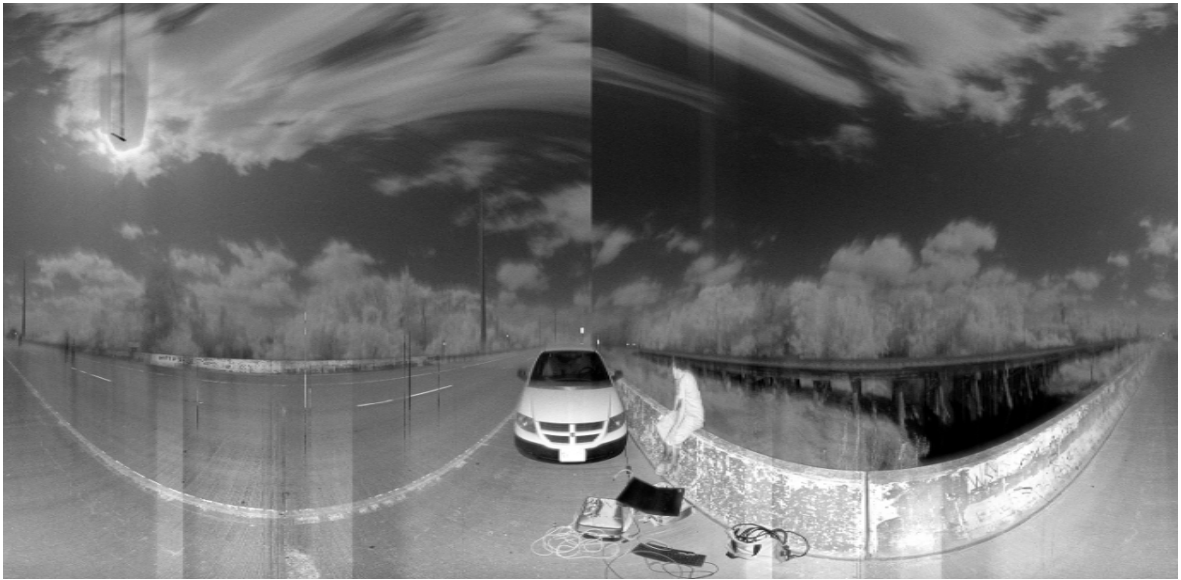


Figure-A102

3D Reconstruction



Figure-A103

IOWA

1. 003826

LiDAR Scan



Figure-A104

3D Reconstruction



Figure-A105

2. 012491

LiDAR Scan



Figure-A106

3D Reconstruction

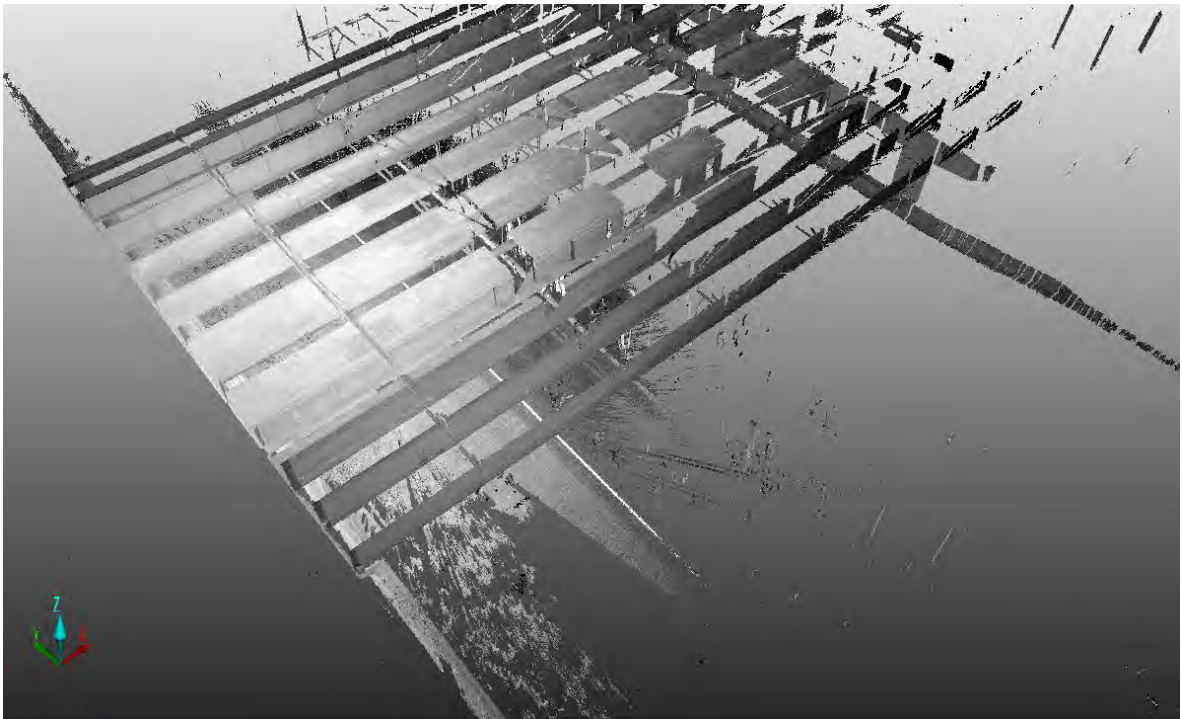


Figure-A107

3. 040390

LiDAR Scan (1)



Figure-A108

3D Reconstruction

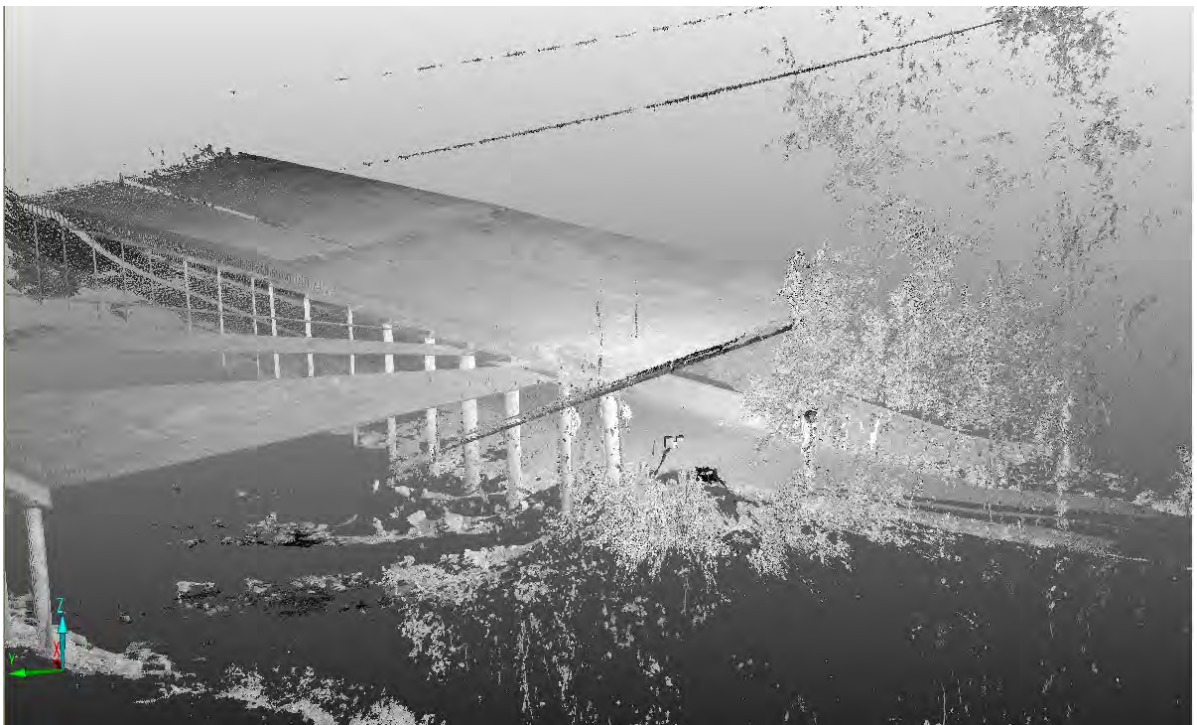


Figure-A109

040390

LiDAR Scan (2)



Figure-A110

3D Reconstruction

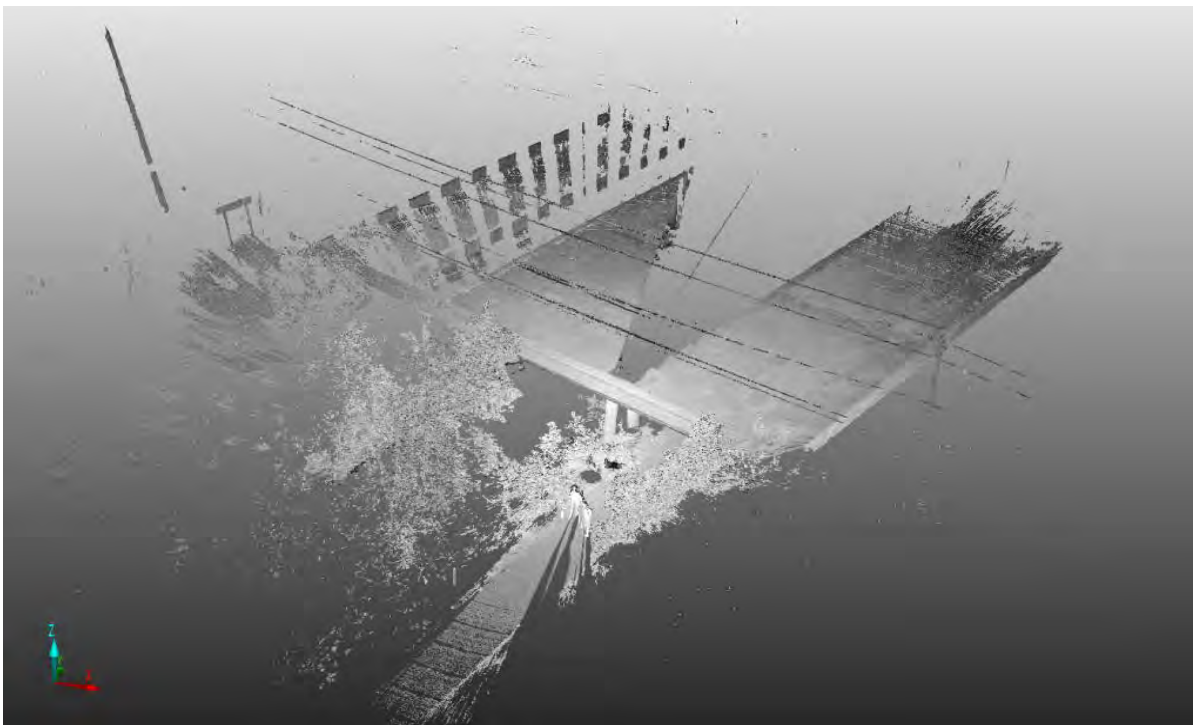


Figure-A111

4. 040510

LiDAR Scan (1)



Figure-A112

3D Reconstruction

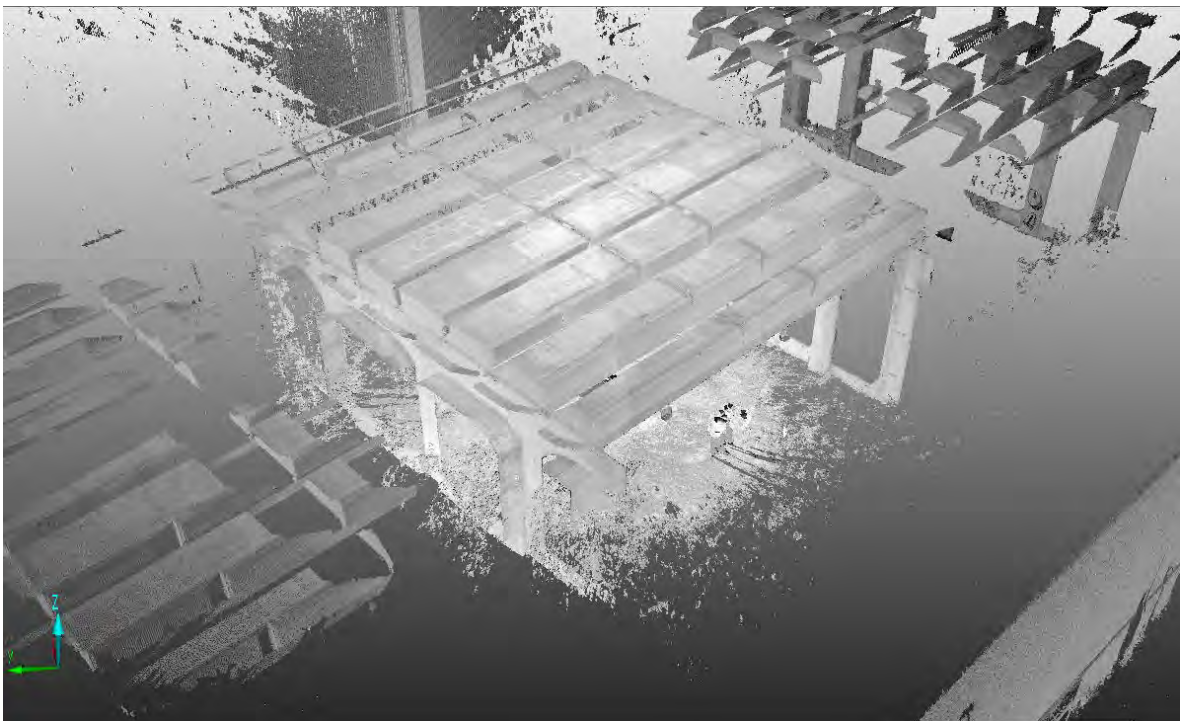


Figure-A113

040510

LiDAR Scan (2)



Figure-A114

3D Reconstruction

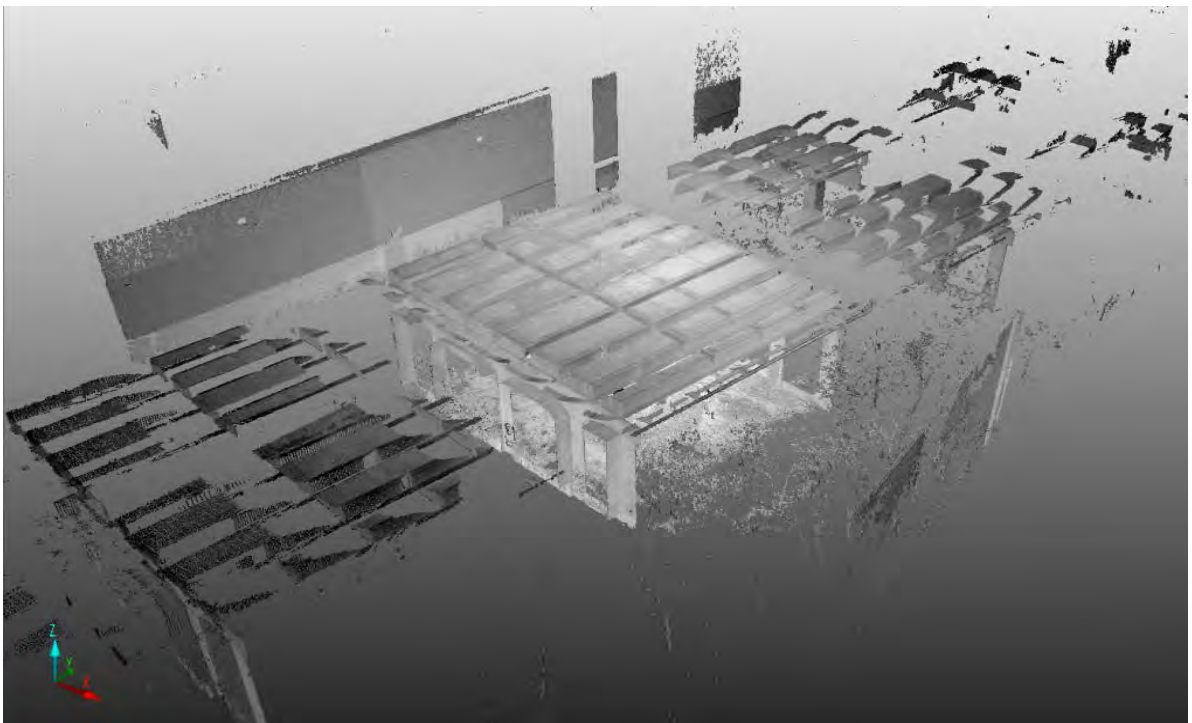


Figure-A115

040510

LiDAR Scan (3)



Figure-A116

3D Reconstruction

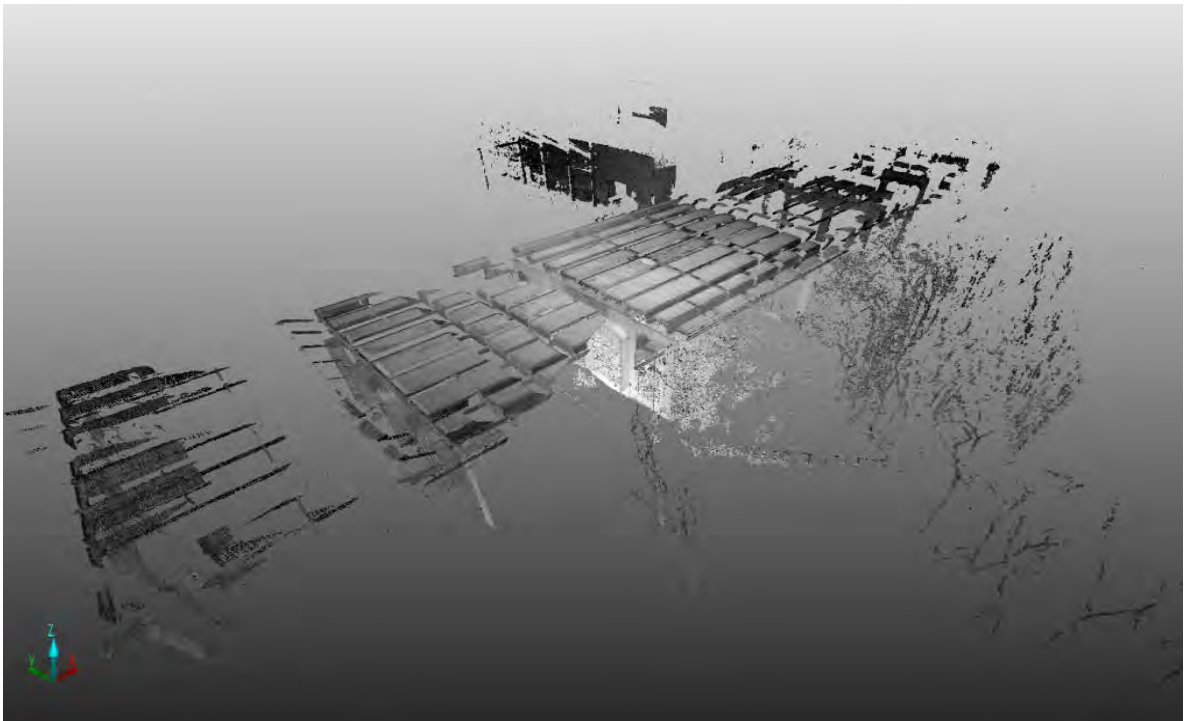


Figure-A117

5. 041300/041310

LiDAR Scan



Figure-A118

3D Reconstruction

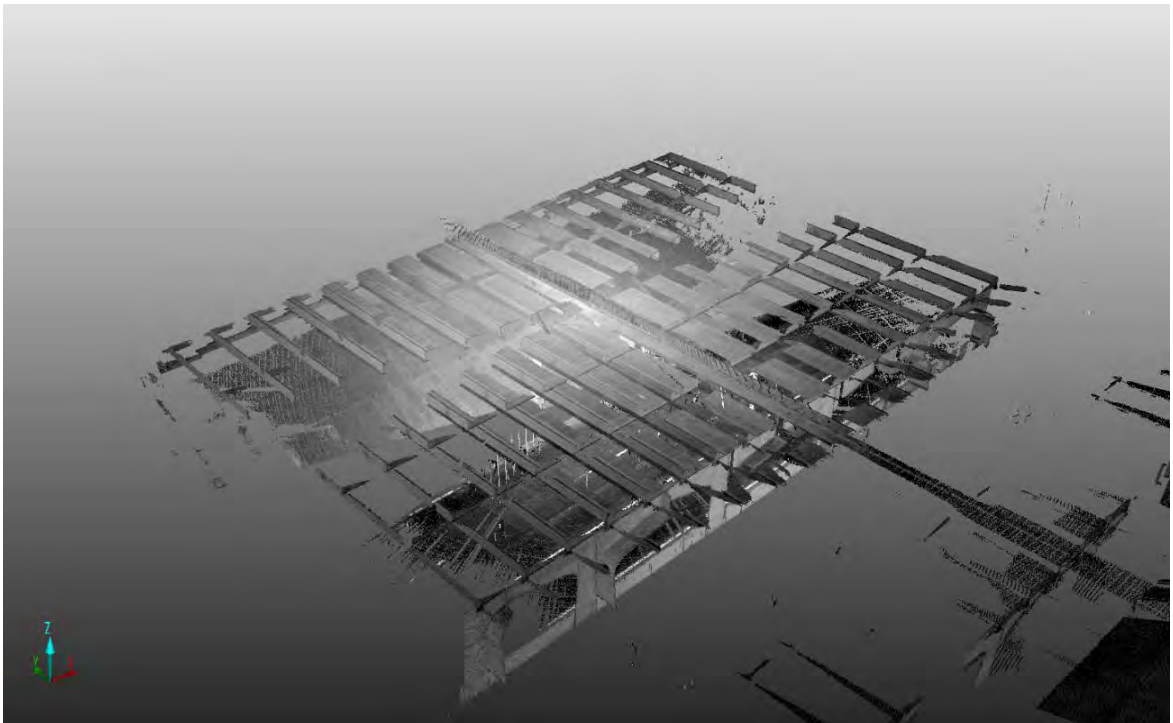


Figure-A119

6. 042300-042310

LiDAR Scan



Figure-A120

3D Reconstruction

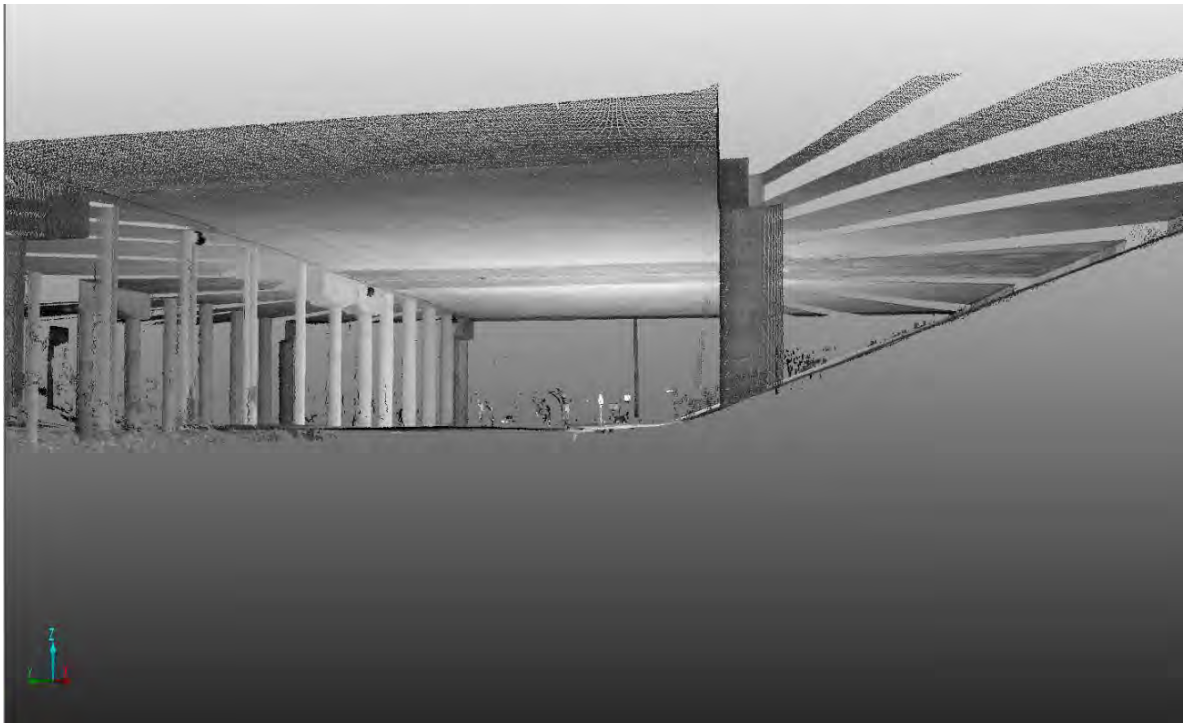


Figure-A121

7. 042381/042391

LiDAR Scan



Figure-A122

3D-Reconstruction



Figure-A123

8. 042401

LiDAR Scan

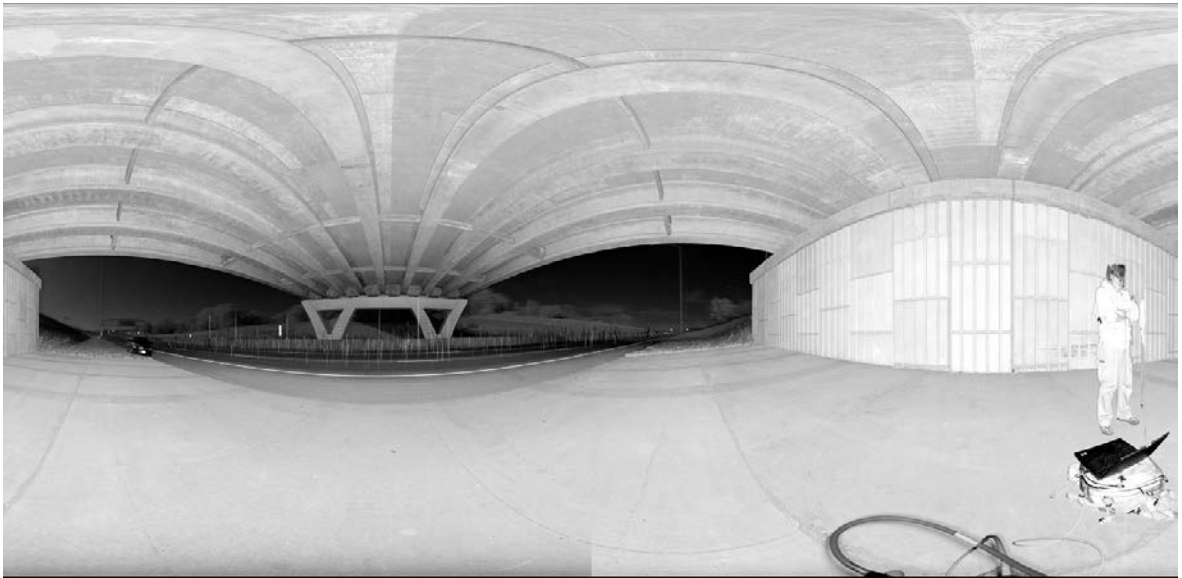


Figure-A124

3D-Reconstruction

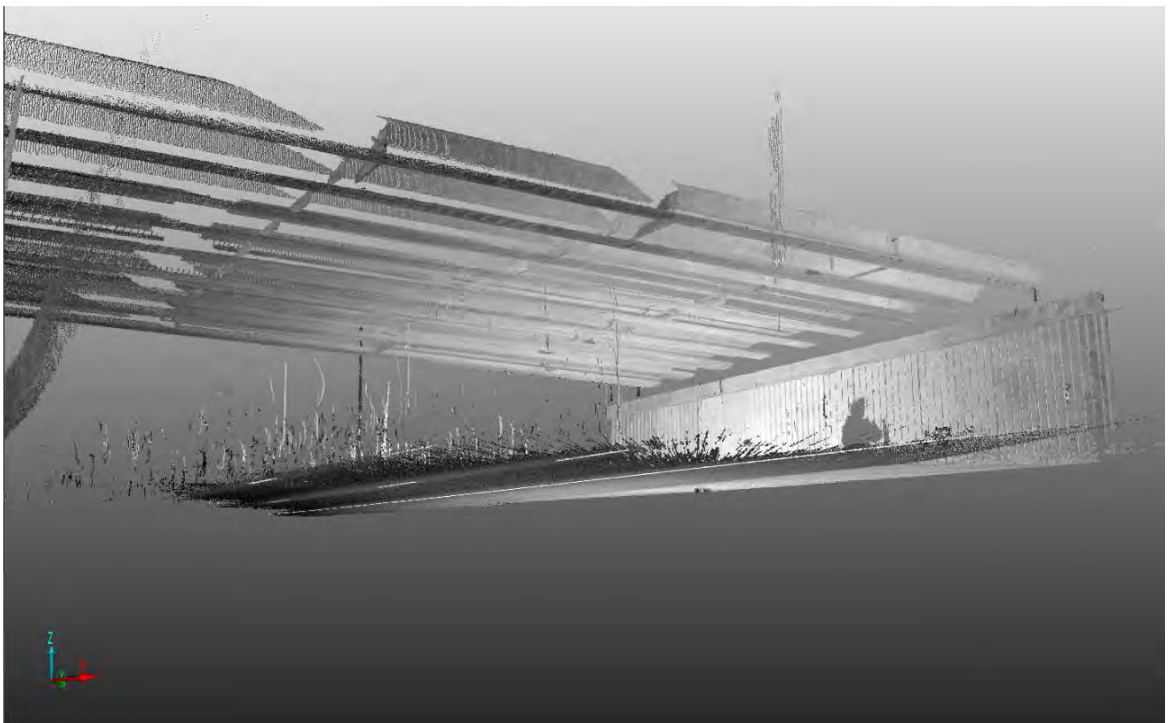


Figure-A125

9. 042761

LiDAR Scan



Figure-A126

3D-Reconstruction

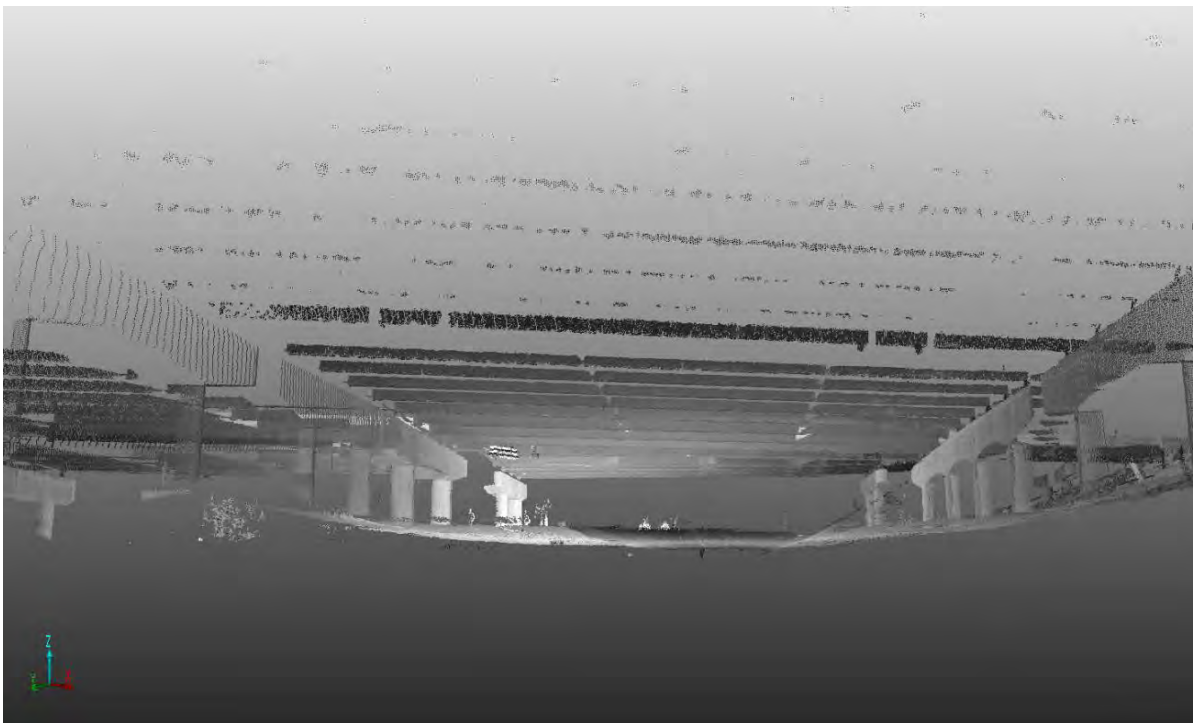


Figure-A127

10. 504480

LiDAR Scan



Figure-A128

3D-Reconstruction

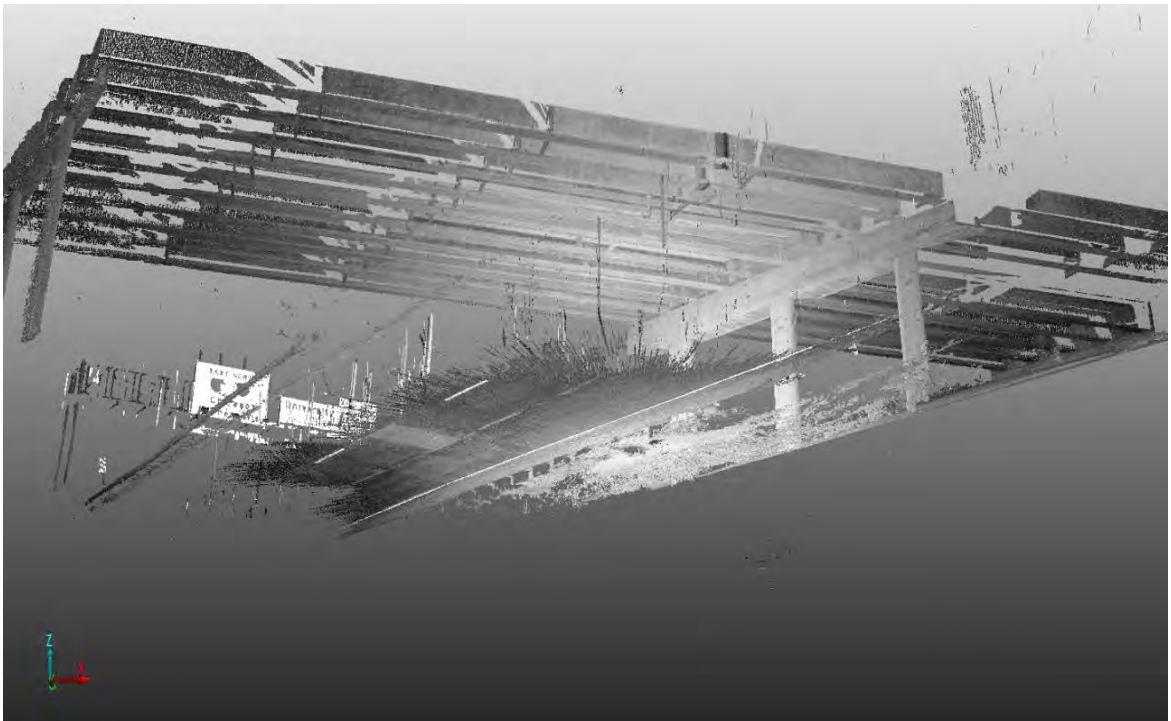


Figure-A129

11. 605405

LiDAR Scan



Figure-A130

3D-Reconstruction

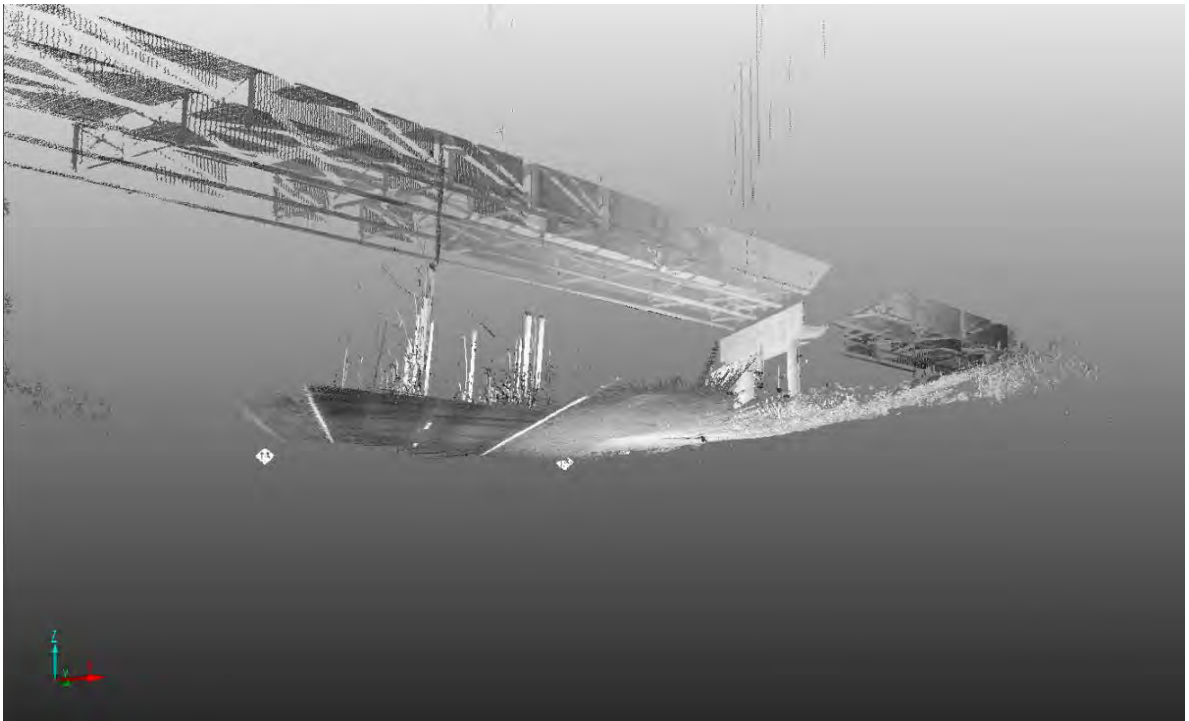


Figure-A131

12. 608345

LiDAR Scan (1)



Figure-A132

3D-Reconstruction

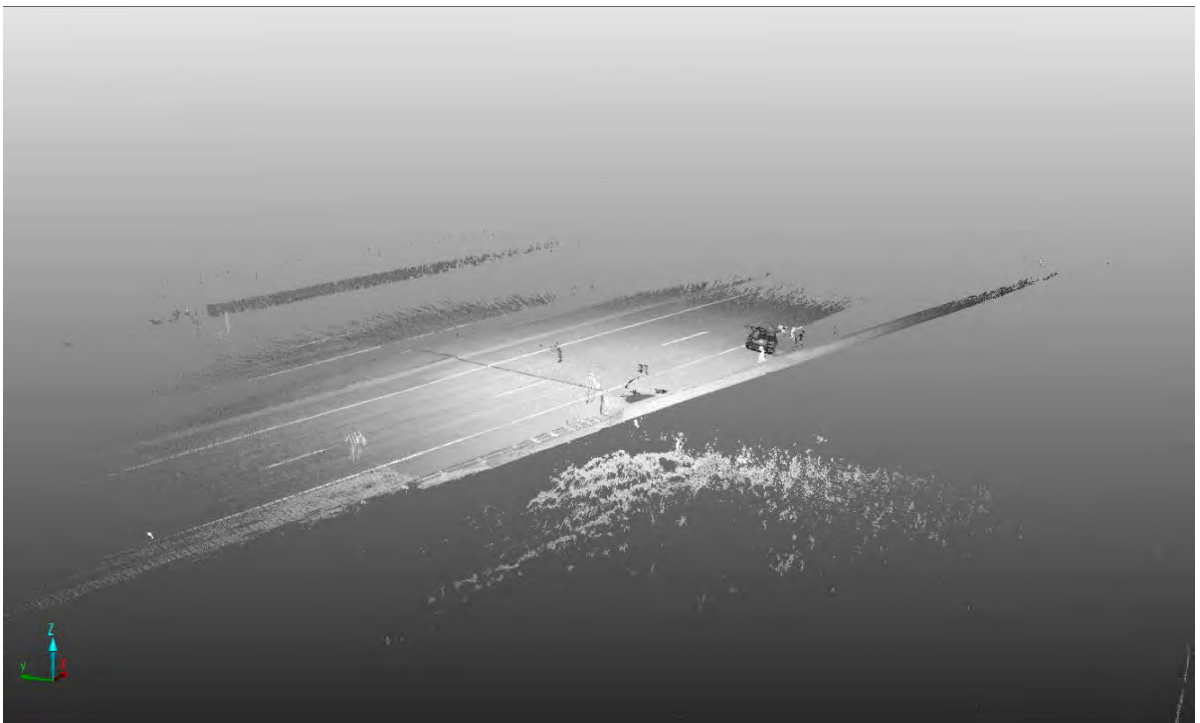


Figure-A133

608345

LiDAR Scan (2)



Figure-A134

3D Reconstruction



Figure-A135

13. 608575

LiDAR Scan



Figure-A136

3D-Reconstruction



Figure-A137

14. 608580

LiDAR Scan



Figure-A138

3D-Reconstruction

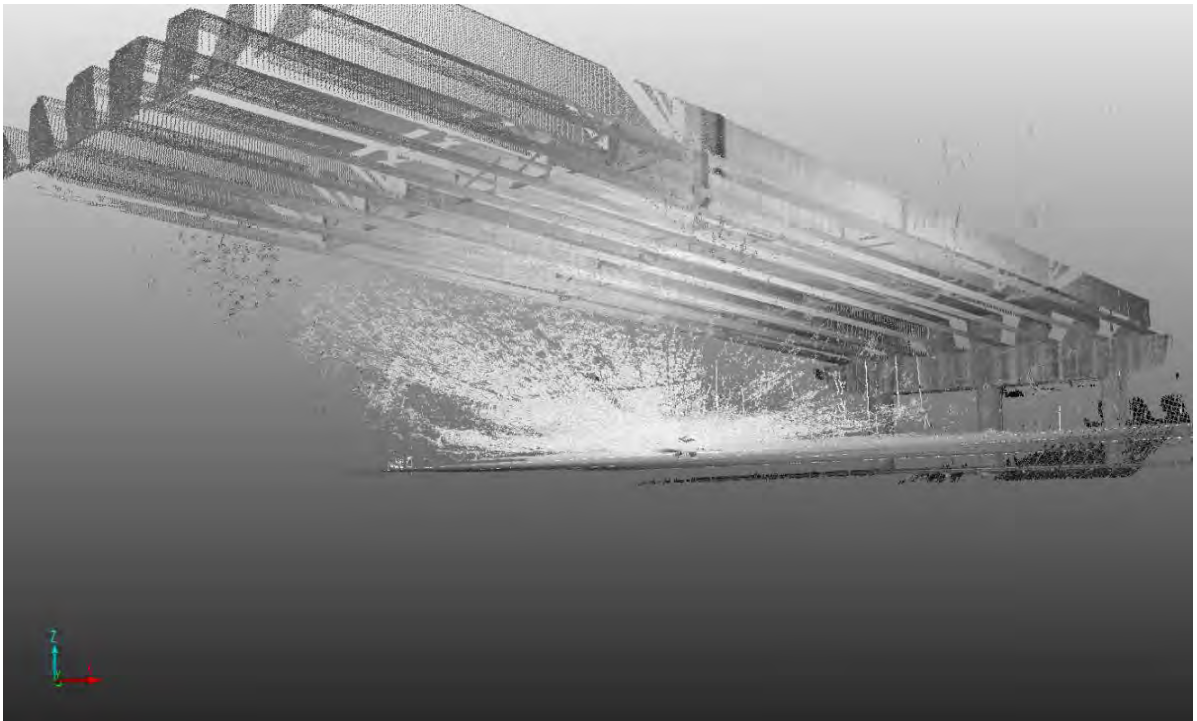


Figure-A139

15. 608660

LiDAR Scan



Figure-A140

3D-Reconstruction

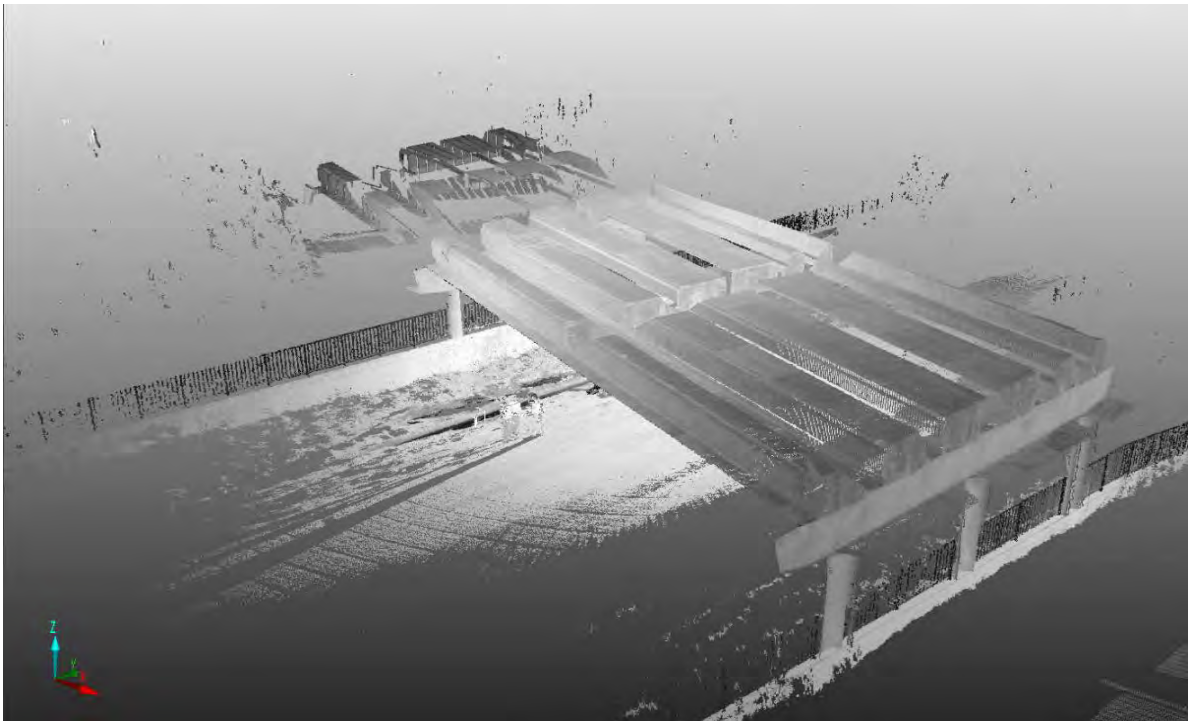


Figure-A141

16. 608665

LiDAR Scan



Figure-A142

3D-Reconstruction



Figure-A143

NEW YORK

1. 1005220

LiDAR Scan



Figure-A144

3D Reconstruction



Figure-A145

2. 1006370

LiDAR Scan



Figure-A146

3D Reconstruction



Figure-A147

3. 1007140

LiDAR Scan



Figure-A148

3D Reconstruction

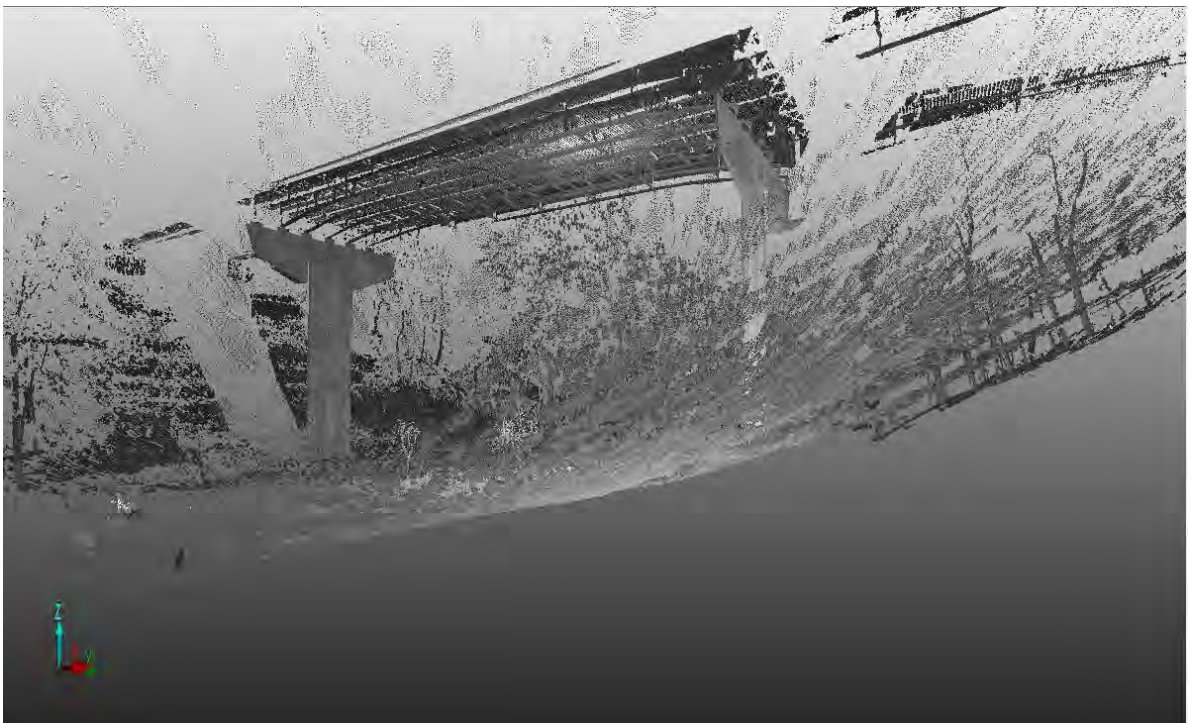


Figure-A149

4. 1007150

LiDAR Scan

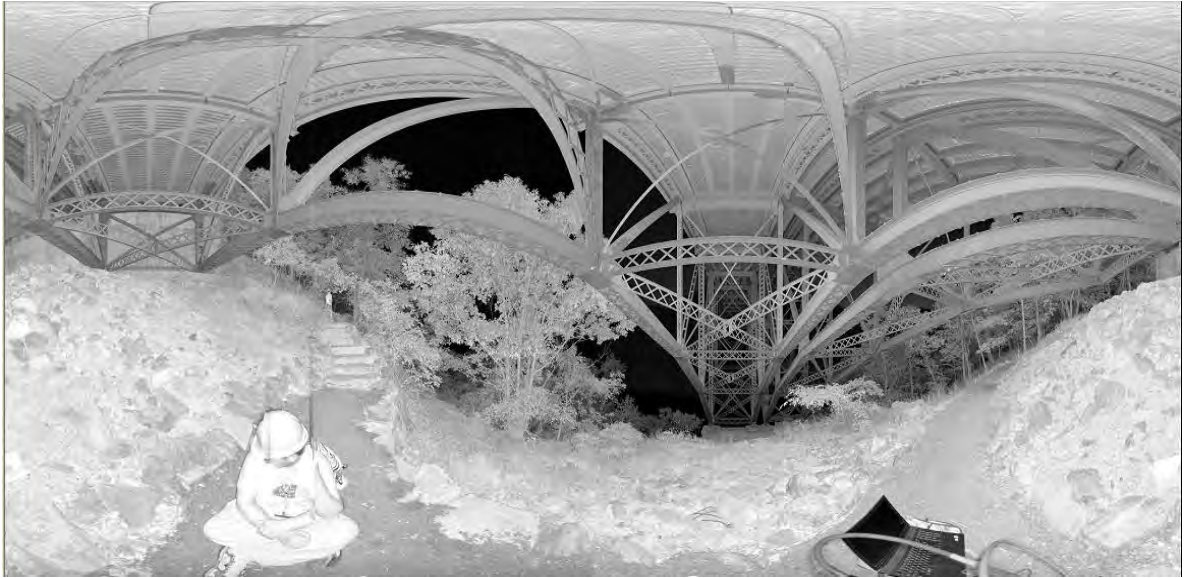


Figure-A150

3D Reconstruction



Figure-A151

5. 1007260

LiDAR Scan



Figure-A152

3D Reconstruction

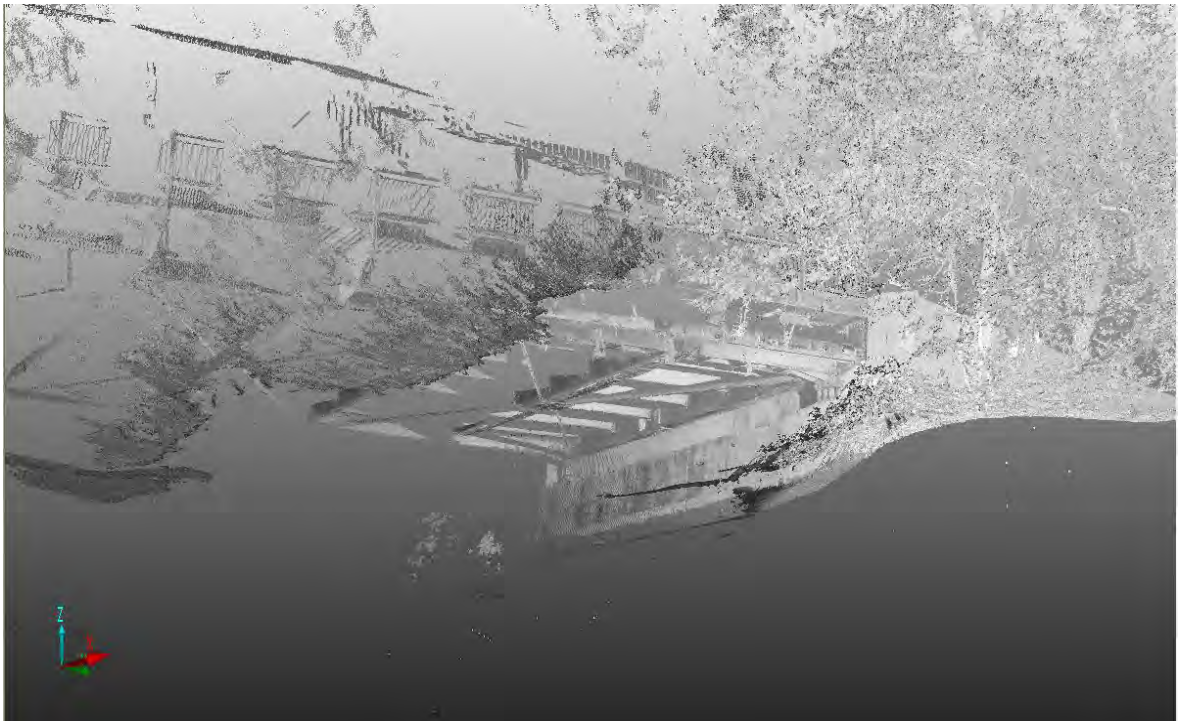


Figure-A153

6. 1014090

LiDAR Scan



Figure-A153

3D Reconstruction



Figure-A154

7. 1027090

LiDAR Scan

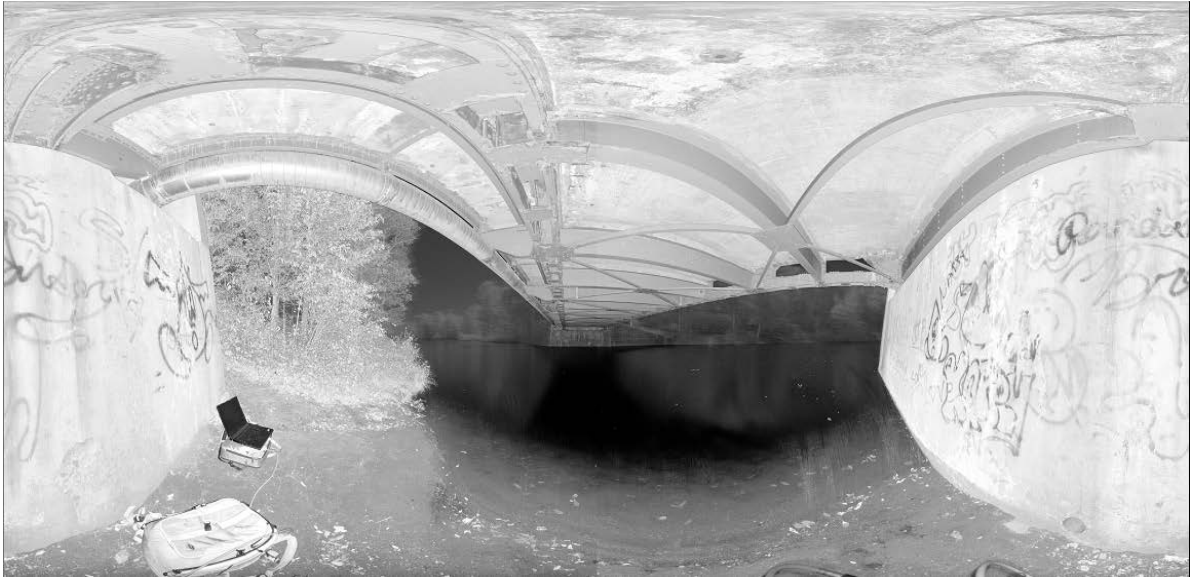


Figure-A155

3D Reconstruction



Figure-A156

8. 1034880

LiDAR Scan



Figure-A157

3D Reconstruction



Figure-A158

9. 1044659

LiDAR Scan (1)



Figure-A159

3D Reconstruction



Figure-A160

1044659

LiDAR Scan (2)



Figure-A161

3D Reconstruction



Figure-A162

1044659

LiDAR Scan (3)



Figure-A163

3D Reconstruction



Figure-A164

10. 1052842

LiDAR Scan



Figure-A165

3D Reconstruction

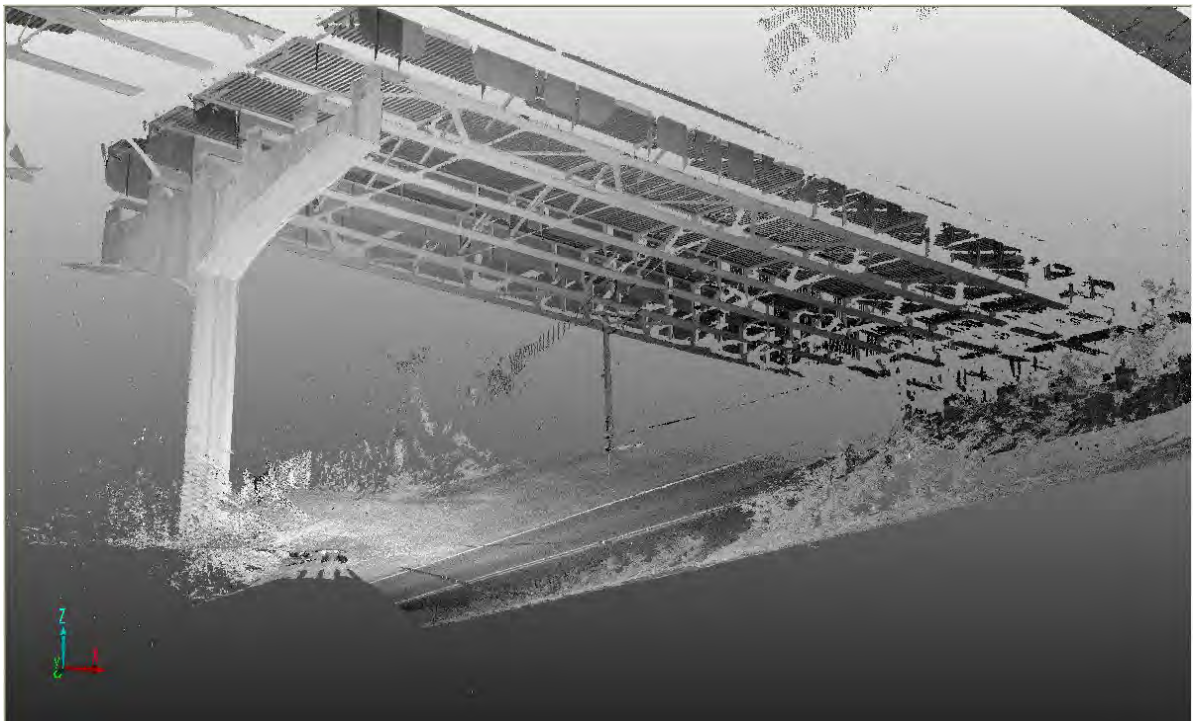


Figure-A166

11. 1069749

LiDAR Scan

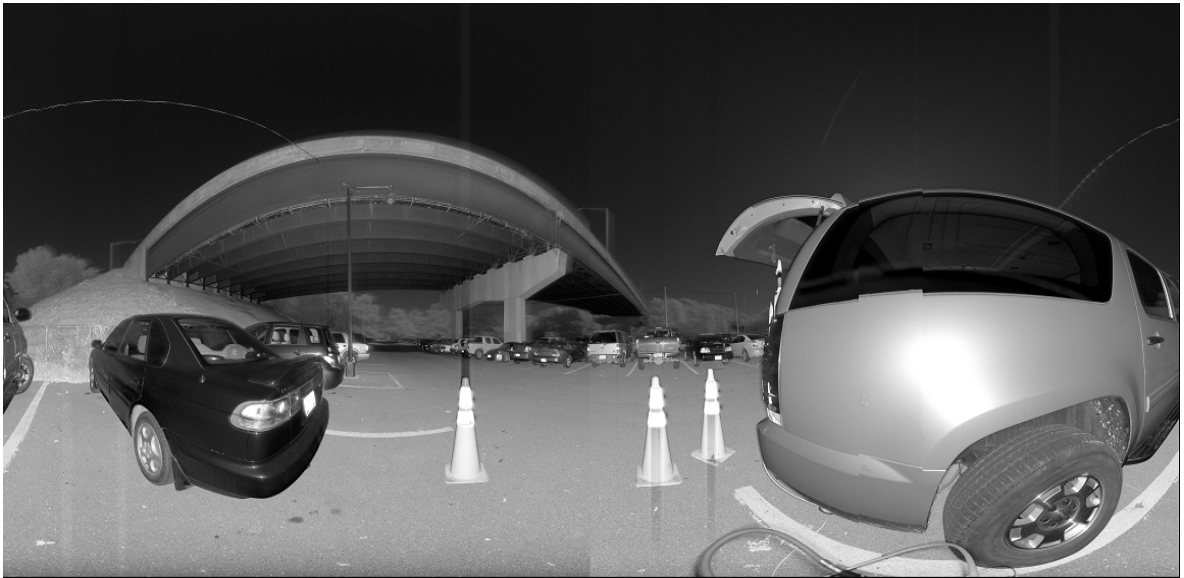


Figure-A167

3D Reconstruction

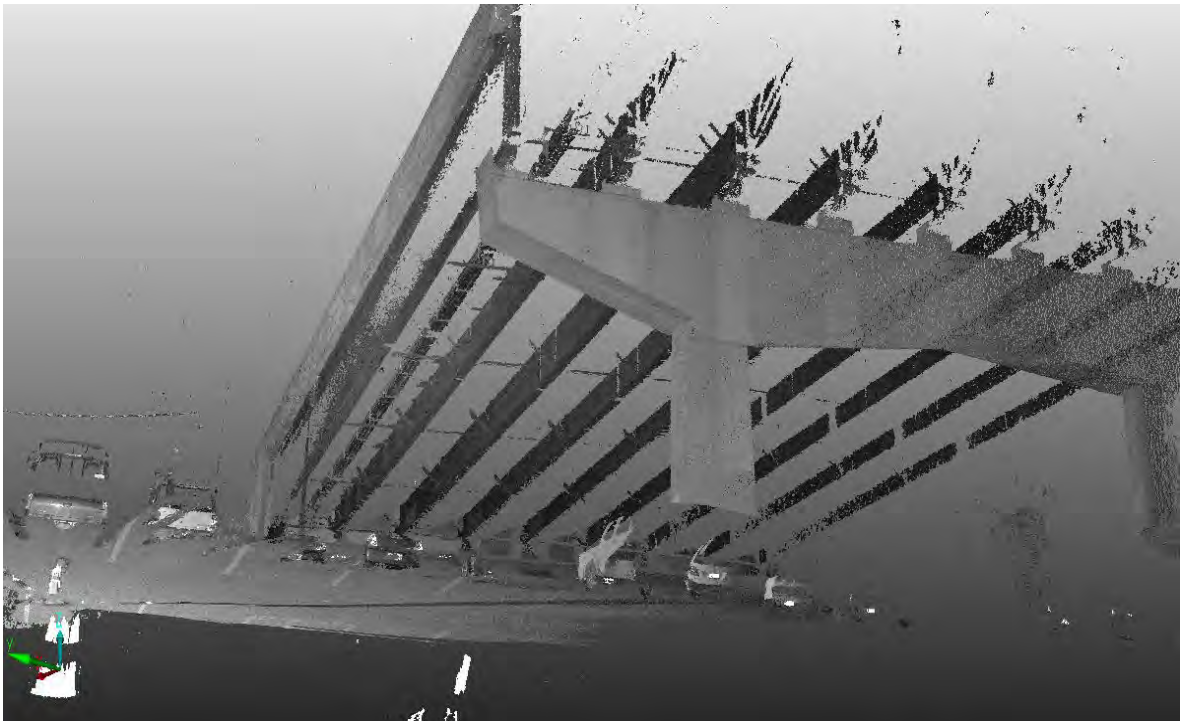


Figure-A168

12. 1070139

LiDAR Scan



Figure-A169

3D Reconstruction



Figure-A170

CALIFORNIA

1. 53C1527

LiDAR Scan (1)



Figure-A171

3D Reconstruction

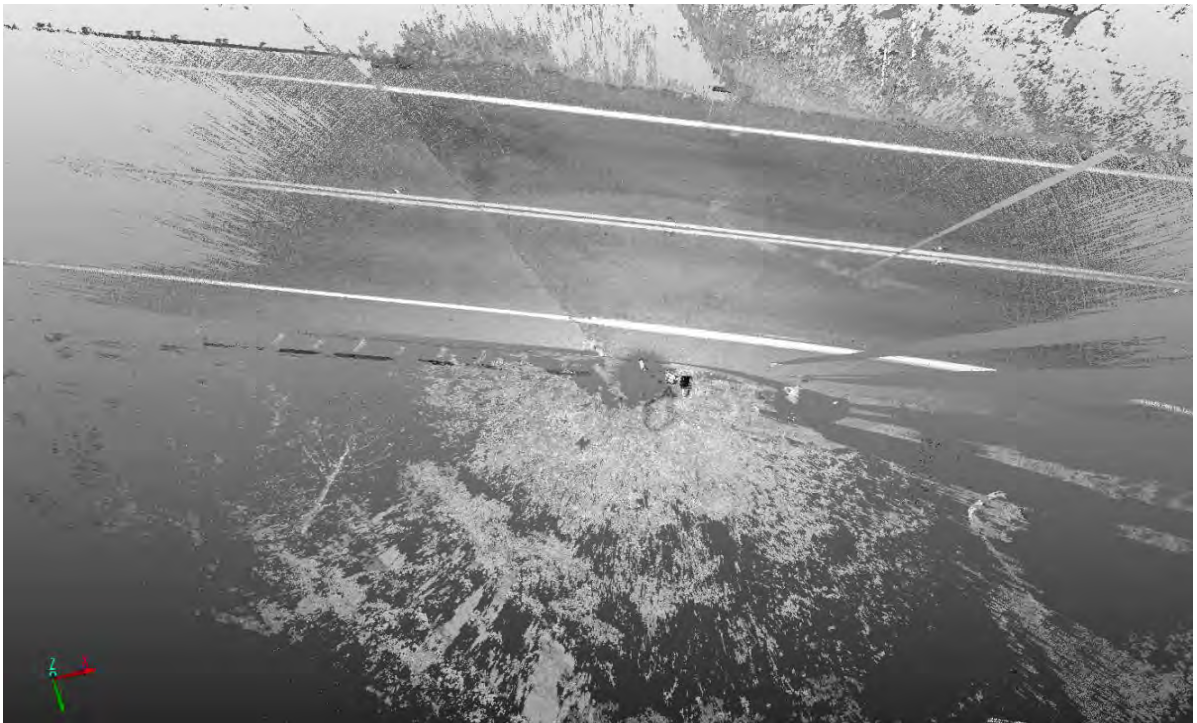


Figure-A172

53C1527

LiDAR Scan (2)



Figure-A173

3D Reconstruction

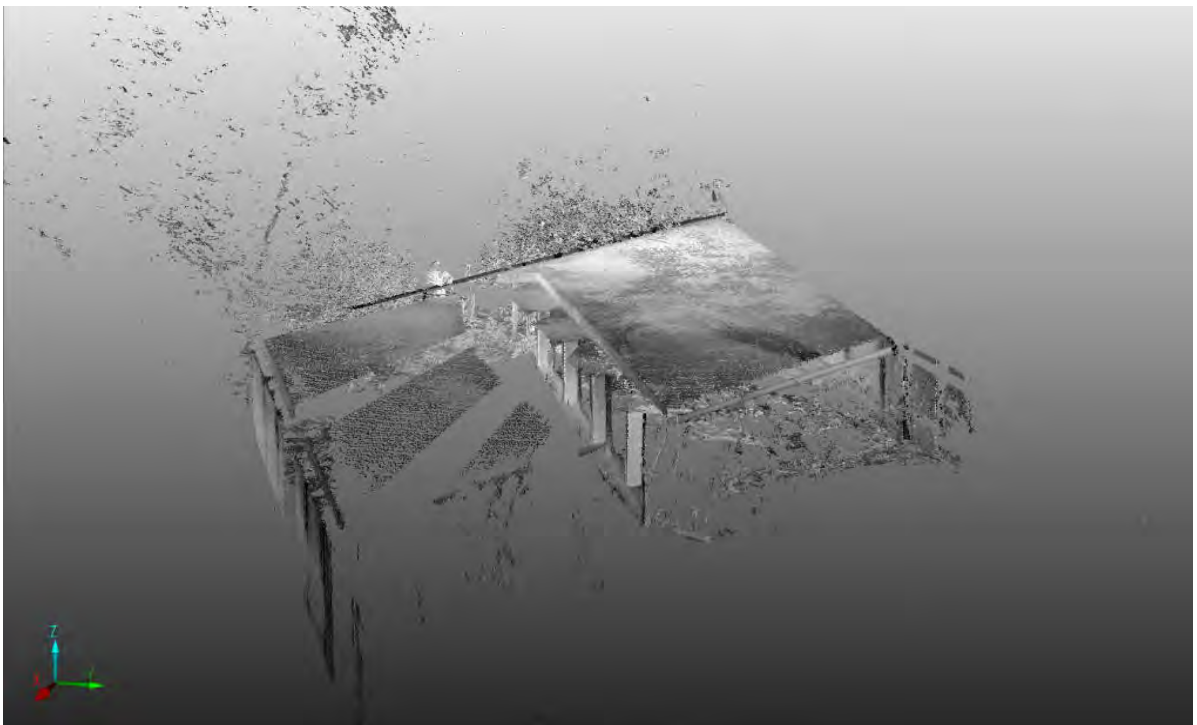


Figure-A174

2. 53C1008

LiDAR Scan



Figure-A175

3D Reconstruction



Figure-A176

3. 53C0981

LiDAR Scan

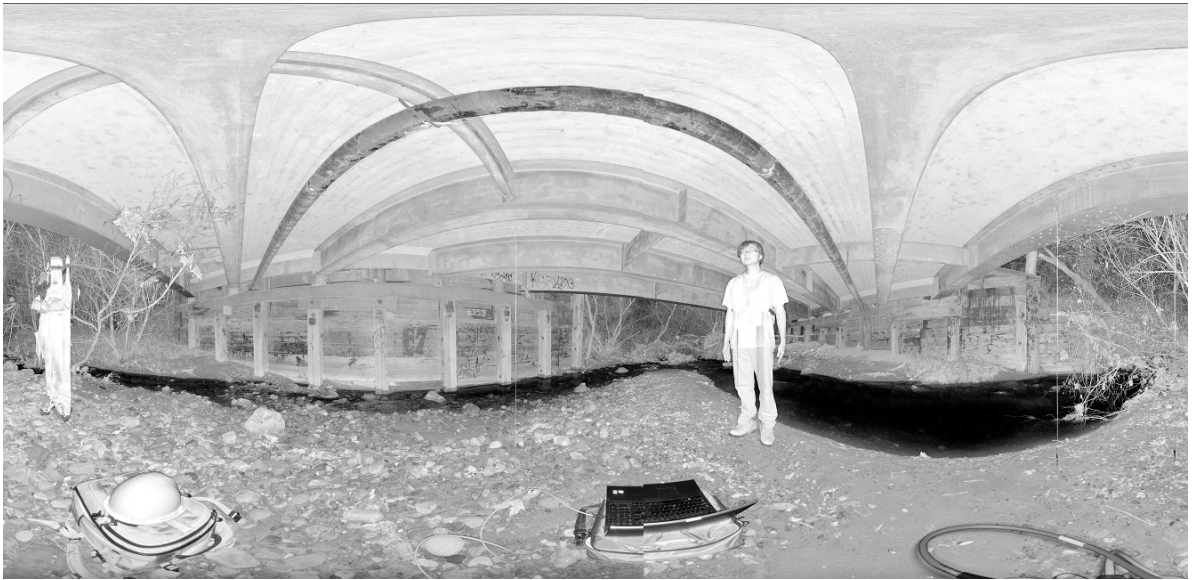


Figure-A177

3D Reconstruction

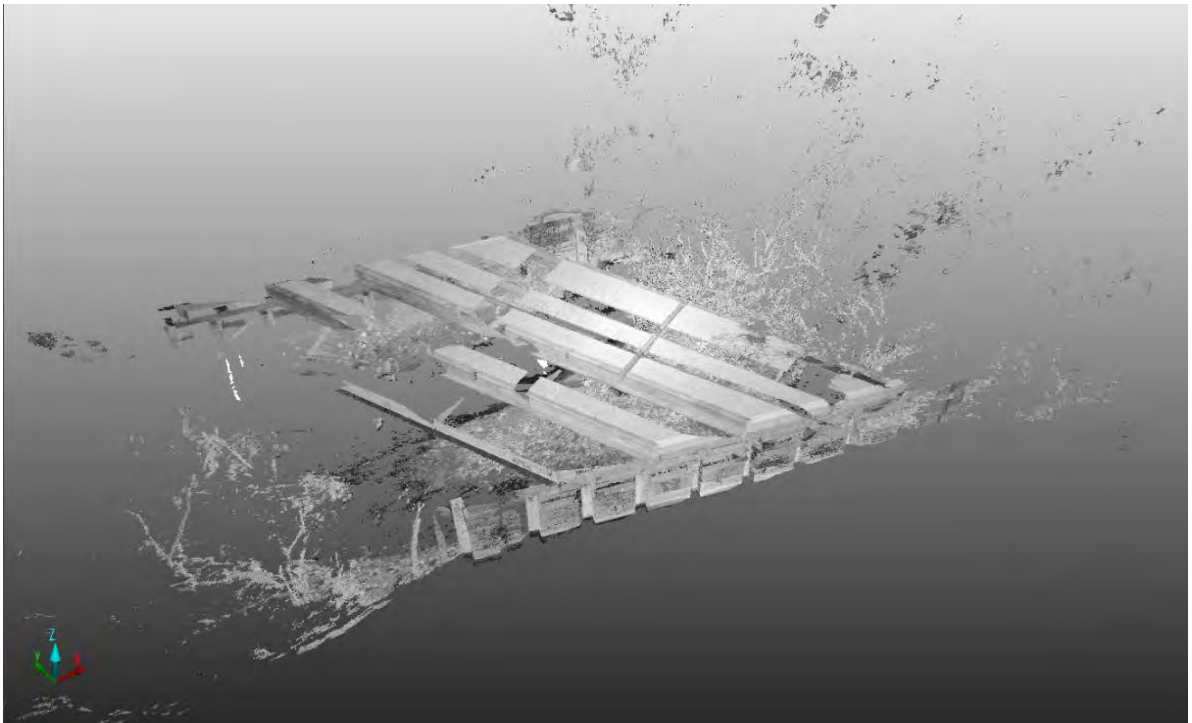


Figure-A178

4. 53C0825

LiDAR Scan



Figure-A179

3D Reconstruction

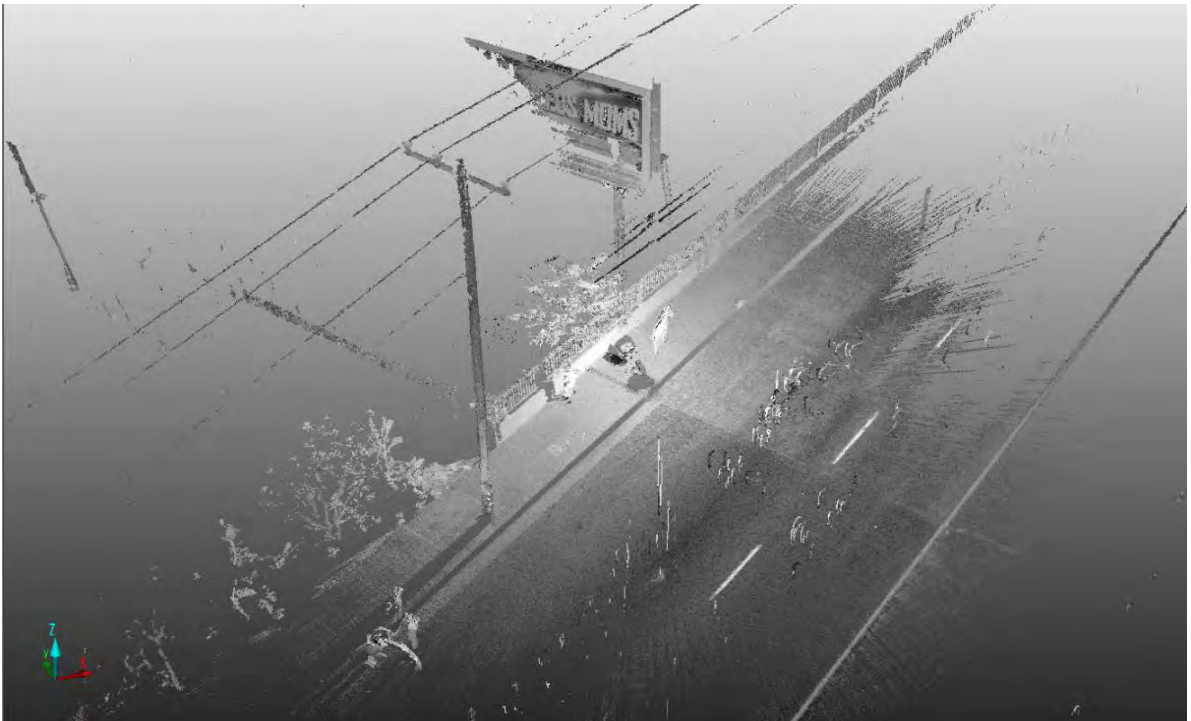


Figure-A180

5. 53C0775

LiDAR Scan



Figure-A181

3D Reconstruction



Figure-A182

6. 53C0642

LiDAR Scan (1)



Figure-A183

3D Reconstruction

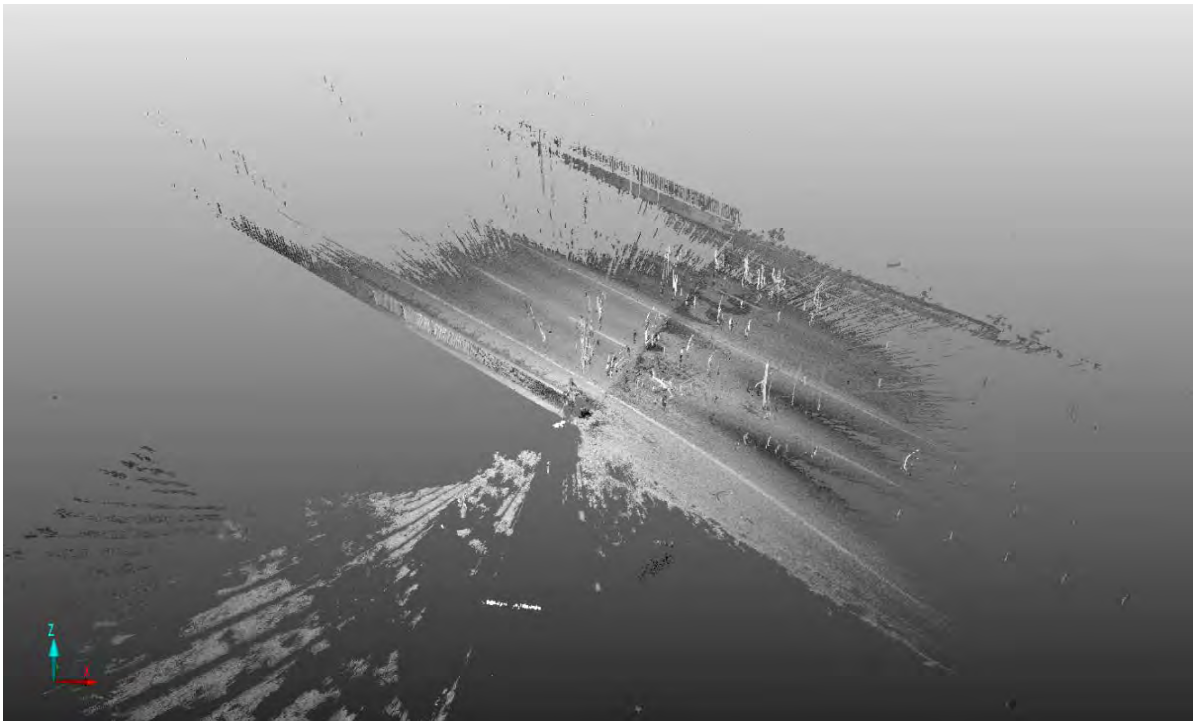


Figure-A184

53C0642

LiDAR Scan (2)



Figure-A185

3D Reconstruction

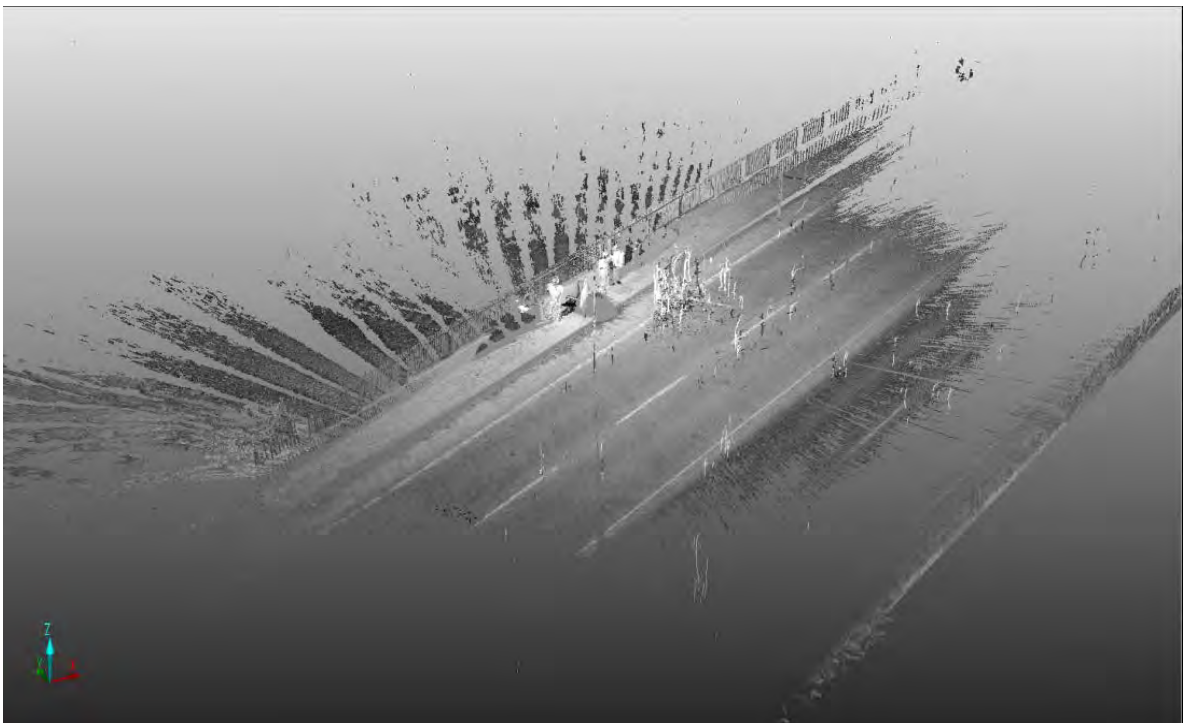


Figure-A186

53C0642

LiDAR Scan (3)



Figure-A187

3D Reconstruction



Figure-A188

7. 53C0625

LiDAR Scan



Figure-A189

3D Reconstruction



Figure-A190

8. 53C0620

LiDAR Scan



Figure-A191

3D Reconstruction



Figure-A192

9. 53C0617

LiDAR Scan



Figure-A193

3D Reconstruction

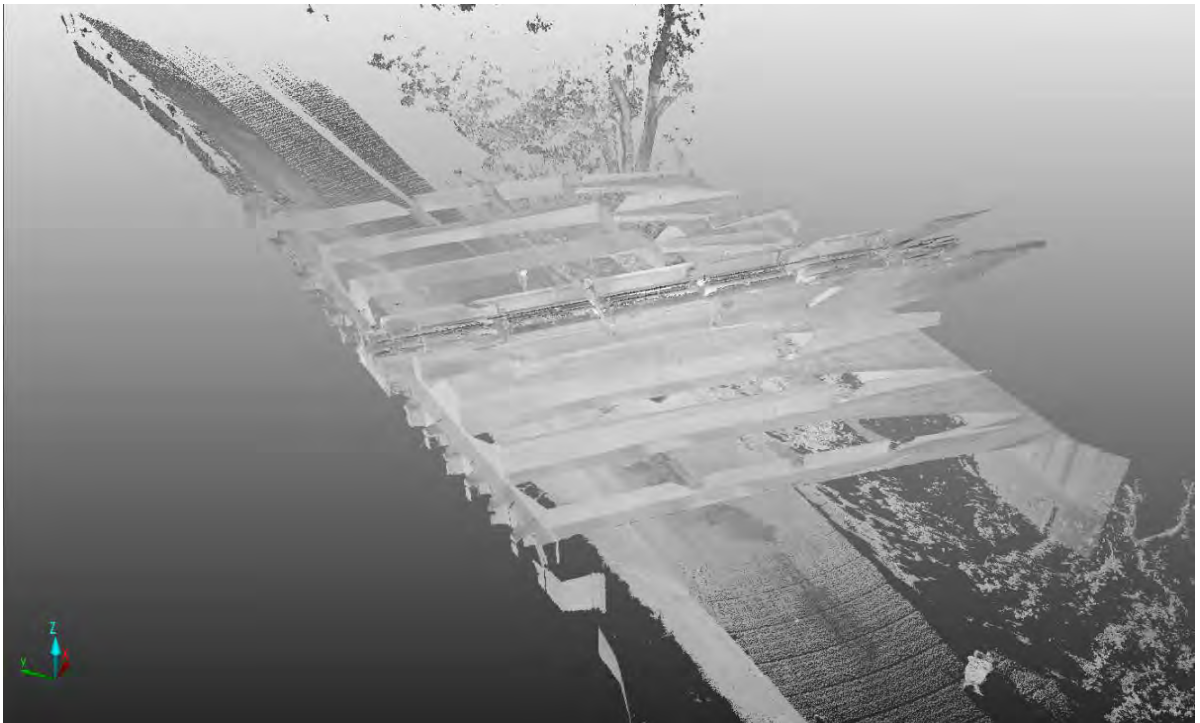


Figure-A194

10. 53C0602

LiDAR Scan



Figure-A195

3D Reconstruction



Figure-A196

11. 53C0470

LiDAR Scan



Figure-A197

3D Reconstruction



Figure-A198

12. 53C0431

LiDAR Scan



Figure-A199

3D Reconstruction



Figure-A200