# A Robust Registration Algorithm for Automatic and Reliable Geometric Change Detection of Bridges using 3D Laser Scanning Data

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Word count: 5929 words text + 6 tables/figures x 250 words (each) = 7429 words

Submission Date: March 8th, 2017

**ABSTRACT**

United States transportation infrastructure facilities, such as bridges, currently have a grade of C+ according to the ASCE annual report card. Long-term spatial changes of bridges can be important precursors of serious structural accidents. Visual inspection methods rely on the experience of engineers for assessing the spatial changes of bridges, but subjective manual change inspection introduces several uncertainties due to the lack of detailed spatial data and comprehensive change analysis methods. 3D laser scanning technology enables change analyses of structures by comparing 3D imageries collected at different times. The challenge of using 3D laser scanning in bridge change analysis is that existing algorithms for point cloud registration are for aligning data sets collected in a scene where no changes occur. Applying these algorithms for aligning data sets that contain long-term changes of bridges using data collected from different times require engineers to manually select parts of environments that do not change before the algorithm can reliably assess changes. Some studies tried to setup control network in the field to overcome this challenge, but maintaining a control network that would not change between data collection sessions could be time-consuming and difficult for outdoor bridge jobsites. This paper presents a robust point cloud data registration algorithm that accurately registers two sets of 3D laser scanning data sets collected at different years and contains changes. The results indicate that this new 3D data registration approach can accurately register the 3D laser scanning data sets collected from different years for effective bridge change analysis.

*Keywords:* 3D Laser scanning, Robust Registration, Change Analysis, Structural Health Monitoring

## INTRODUCTION

Transportation infrastructure facilities such as bridges are deteriorating at an alarming rate due to continuous spatial changes such as deformation or deflection of the bridge elements *(1)*. Uncertainties in predicting the exact deterioration rates for bridges can lead to loss of life and property *(2)*. Transportation Research Boarc (TRB) utilizes a transportation asset management (AM) framework for strategic maintaining, managing, and upgrading physical assets such as civil infrastructures through their life cycle *(3,4)*. Migliaccio et al. conducted a study on the data quality assessment and improvement framework for improving the quality of data collection activity on transportation assets *(5)*. Samali et al. highlighted the importance of gathering and analyzing bridge condition data for the bridge management system for predicting the condition of bridges using a data-driven decision making and plan for maintenance funding *(6)*. Several studies also stated the need for reliable sensor data-driven decision making in the bridge management system for accurately assessing the health of a bridge structure and for performing risk based asset management studies *(7)*. In general, traditional surveying technologies collect three-dimensional (3D) measurements at manually selected 3D surveying locations to aid engineers in identifying geometric changes of structures. Unfortunately, such methods (e.g., total stations) could hardly collect dense geometric measurements and often requires experienced professional to interpret the data and accurately identify the damages on a bridge *(8)*. 3D laser scanning technology provides detailed geometric data that facilitate in detecting geometric changes of the bridge during its service period. However, periodic investigation of the bridge structure using 3D laser scanning data requires manually aligning two sets of point cloud data collected at different times. Such aligned process is termed as registering two point cloud data sets into one single coordinate system. However, such manual alignment process may significantly affect the analysis results.

Unreliable or inaccurate registration of 3D laser scanning datasets of a bridge collected at different times (e.g., from year to year, or from month to month) can lead to improper detections of spatial changes and eventually leading to unreliable condition assessment of bridge structures. Failure to accurately detect spatial changes may lead to incorrect decision-making and wastage of maintenance resources. Traditionally 3D laser scanning data processing software utilize common feature points between several scans of a bridge structure to perform the automatic registration process *(9)*. Based on this principle, several previous studies developed automated algorithms based on robust feature point registration for aligning two sets of 3D laser scanning data *(10,11)*. Such algorithms identify common feature points between two data sets and align them using an Iterative Closest Point (ICP) registration method that minimizes the difference between the two point cloud data sets *(12)*. However, these algorithms were developed for aligning 3D data sets collected within a short time (e.g., within the same day) and need the collected data sets share a significant number of unchanged features (e.g., within the same day, most parts of a job sites remain unchanged). On the other hand, the authors found that the long-term change analysis of bridges requires registration of data sets collected from data collection sessions that are months or even years apart from each other, which can contain large amounts of gradual changes of bridges and environments. Therefore, utilizing conventional feature-based algorithms for registering 3D laser scanning data sets collected from different times can lead to significant registration errors and eventually leads to detecting geometric changes reflected by such registration error. In the next section, the authors provide the details about the steps taken to implement the registration using manual feature point selection and limitations of using traditional registration approach.

**Limitations of traditional registration approach**

This section presents a motivating case to highlight the necessity and contribution of the study described in this paper. Figure 1 shows the 3D laser scanning data of a two-lane pre-stressed concrete bridge located in Mesa, Arizona collected in 2015 and 2016. As per the 2D drawings, the bridge is 396.25 meters long and 13.5 meters wide and consists of 18 spans. Each span is 19.8 meters long that is supported by four 32 meters long columns. The authors first remove the unwanted data in both the 3D laser scanning data sets. Such unwanted data are mostly from objects in the environments, such as trees, hills, traffic noise (moving cars), water under the bridge, etc. Performing the registration with these unwanted data will significantly affect the registration results, as these objects can change significantly compared with bridge structures. The authors manually remove all unwanted data points in both the two 3D laser scanning data sets to be compared using the interactive segmentation tool found in CloudCompare *(13)*. The 3D laser scanning data collected in 2015 consists of around 657 million points whereas the data collected in 2016 consists of about 335 million points. However, both data sets have the same number of scans. Such data collection process shows that the point cloud data collected in 2015 have scans having higher data densities (spatial resolutions), which eventually leads to parts of data having denser and more number of points. During the registration, denser parts of the point clouds provide more data points for matching data from two years, and the algorithm will tend to bias towards those parts having denser point clouds. Automatic registration methods such as Iterative Closest Point *(14)* or registration methods would generate results biased towards denser data parts and high errors in parts of the scene that have sparser or missing data. Figure 1 (a) highlights the denser parts of data collected in 2015. This figure shows that the registration will be biased towards the highlighted areas and produce registration errors in parts that have fewer data points. Primarily, such registration errors will affect the change analysis of the bridge structure and lead to improper decision-making. Therefore, a subsampling method that can generate 3D laser scanning data sets which have similarly distributed points around the point cloud data is thus necessary for overcome this issue (similarly distributed data density between the point cloud data sets).

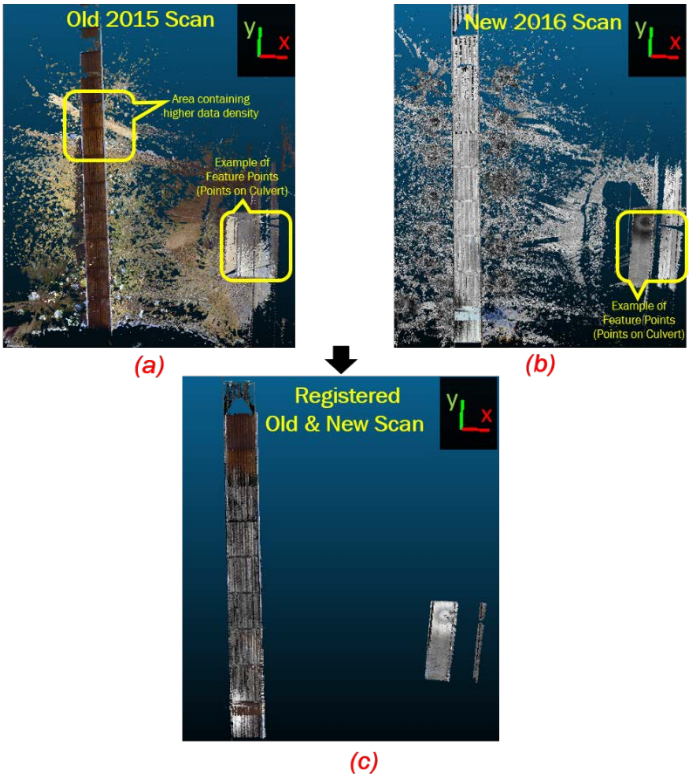


**Figure 1** Registered 3D laser scanning data collected in 2015 and 2016 using traditional approach

Another way to overcome the bias issues caused by varying data densities is to perform registration by manually selecting common feature points between both the 3D laser scanning data sets. Such features include railing ends, signs on bridges, etc. Varying data densities of the point cloud data generally do not affect the traditional registration approach that relies on common feature points because those algorithms only use selected feature points not all the points in the point cloud. Figure 1(a & b) highlights few common feature points that can be utilized for performing the registration between the 2015 and 2016 3D laser scanning data sets using manual feature point selection (Figure 1 (c)). This manual approach can be utilized for change analysis of the bridge structure but has few limitations. First, the amount of time invested in manually selecting common features is high. Another major limitation of this approach is the assumption that the manually selected feature points would not change significantly when compared with changes of the bridge structure. Selecting feature points that have large spatial changes than the bridge structure's changes will mislead the change analysis as well. A novel registration approach that performs reliable registration between two 3D laser scanning data sets containing spatial changes is in need.

Several researchers combined the use of Total Station data, and the data collected the 3D laser scanners to establish a control network of points that would not change. This process involves scanning the bridge structure along with the use of a total station to establish a control network that will not change significantly between the data collection sessions. This process of scanning the bridge structure along with the established control points helps in aligning 3D laser scanning data collected at different times. However, the process of establishing the control network is tedious and becomes impractical when a bridge submerged in water *(15)*.

Additionally, checking and ensuring that at least three control points are visible from any pair of registered laser scans is also tedious and could hardly be practical for complex outdoor jobsites. For instance, scanning a control point that has been setup far away from the bridge structure requires high-resolution scans that generate a large amount of raw data for pre-processing.

This paper presents a novel robust registration approach that automatically registers two sets of 3D laser scanning data collected at different times that are one year apart from each other. First, the approach extract bridge features from two 3D laser scanning point clouds and roughly register two bridge data sets by matching salient bridge features. Next, the algorithm extracts feature points from both the surroundings and on the bridge structure and then use a new robust 3D data registration algorithm that automatically identifies changed features between two data sets through a robust fitting method. Finally, the algorithm utilizes the robustly registered feature points to perform accurate registration of the point clouds and label changed parts between two point clouds. The authors tested this robust registration approach using 3D laser scanning data of a highway bridge collected in 2015 and 2016 respectively. The following section briefly reviews previous studies on conventional 3D data registration methods (Section 2). The authors describe the developed methodology in detail in Section 3 and present registration results of the new method on the data collected on a highway bridge in Section 4. The authors then validate the new approach by comparing it with conventional 3D data registration method that uses manually selected feature points for aligning 3D data sets from different data collection sessions (Section 5). Finally, the paper concludes by summarizing the results and discussing the limitations (Section 6).

## LITERATURE REVIEW

Bridges undergo several spatial changes during its service period. These changes have to be periodically detected and analyzed to identify the abnormal changes affecting the bridges loading behaviors. Recent developments in the field of computer vision (2D & 3D imagery data) applications in civil engineering enable spatiotemporal information retrieval from imagery data for engineering decision support on construction sites *(16)*. Spatiotemporal changes observed in point cloud data sets collected at different times provides detailed visual information for monitoring changes and analyzing structural deformations *(17,18)*. Lindenbergh and Pfeifer utilized terrestrial laser data of a lock (sea entrance of a harbor) for statistical deformation analysis *(19)*. The statistical analysis consists of calculating the deformation of the lock detected between two point clouds scanned at the exact same position. Such analysis concluded that terrestrial laser scanners could achieve deformation detection in the order of 9 mm. However, the major limitation of the statistical analysis study for deformation monitoring is that the researchers conducted the experiment by fixing the scanner's position. This is a limitation in cases having to detect deformation of civil structures at larger time gaps and unable to access previous scan position for the next data collection. Numerous studies conducted change detection studies using two sets of point cloud data scanned within 24 hours *(18)*. Girardeau-Montaut et al. detected changes between two sets of point cloud data collected every day *(18)*. The change detection study utilized the point cloud data to monitor applications on a building site by registering two 3D laser scanning data sets having shared points nearly not moved. Such registration process consists of using a minimum threshold value for the shared points and then utilizing the Iterative Closest Point (ICP) approach to perfectly align them. The major disadvantage of using such approach is to detect changes in structures that undergo significant spatial changes over the time period such as a bridge structure.

Researchers also conducted studies to monitor complex deformation of objects having complicated shapes *(20–22)*. Antova *(20)* discussed several registration processes that can

perform deformation monitoring using laser scan data in the field containing objects having complicated shapes. These registration processes automatically generate targets using planes in overlapped scanned for performing the registration. However, the accuracy of the registration results is dependent on the percentage of overlapping between the scans. Other studies involved combining terrestrial laser scanning technology with static GNSS positioning and Tacheometry point-wise surveying techniques. Vezocnik et al. conducted long-term high precision deformation monitoring of underground pipelines subjected to high-pressure conditions and concluded that the combined use of laser scanning and point surveying techniques is a valid solution for monitoring deformation in a 3D space *(21)*. The limitation of using such techniques is the amount of time invested in the data acquisition and processing and in assuming that the selected surveying point do not change over a few months. Therefore, the authors developed a novel robust registration approach to reduce the amount of time needed in data acquisition and to accurately register 3D laser scanning data collected at different times. The following section presents the developed approach in detail.

## METHODOLOGY

The developed robust registration algorithm automatically registers two sets of 3D laser scanning data collected in different years (Figure 2). It utilizes points that are common and are less likely to change between two 3D laser scanning data sets of the bridges and registers them into one global coordinate system. The major advantage of this robust registration algorithm is that it automatically identifies such common points that do not have significant changes between two years' data. These automatically identified points aid in performing reliable registration of the two 3D laser scanning point clouds in order to accurately detect the geometric changes of bridges from year to year. The first step in the robust registration approach is to perform rough registration of the two 3D laser scanning data sets. This rough registration can be either performed manually or using commercially available registration software tools (e.g., Leica Cyclone). Next, the authors manually remove redundant data found in 3D laser scanning data. Inaccurate segmentation of such redundant data may cause unreliable registration. The following section details the data preprocessing and 3D point cloud subsampling process.

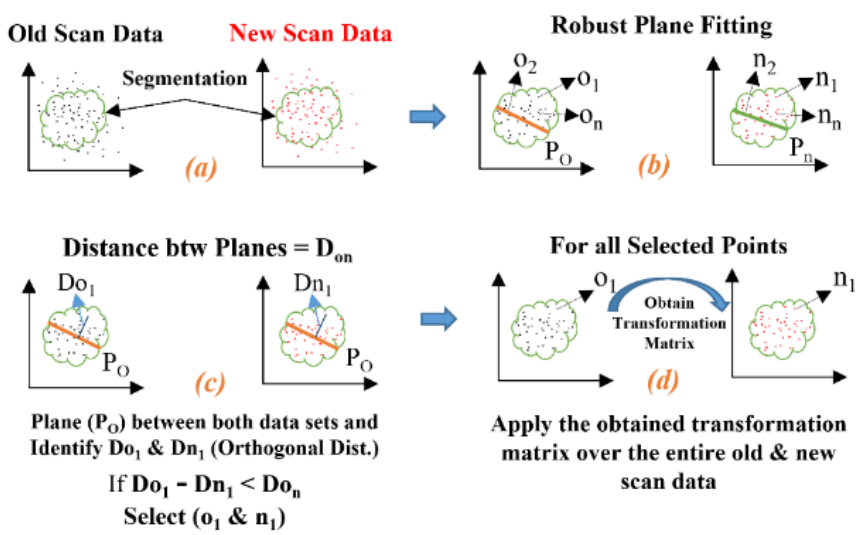


**Figure 2** Robust registration approach to register old and new scan data

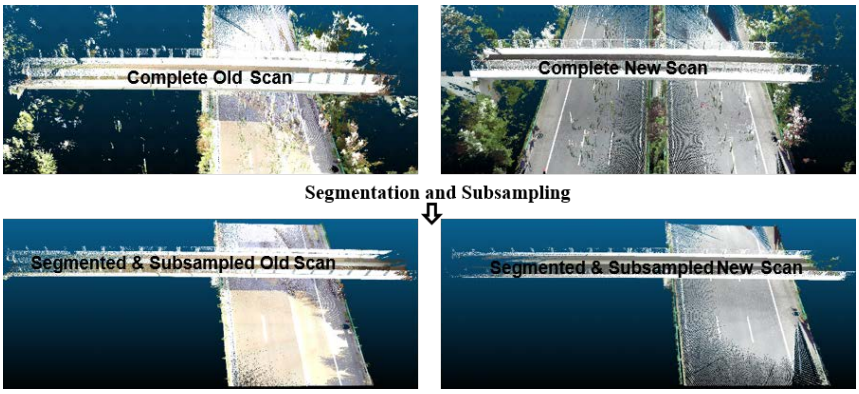


**Figure 3** Segmentation and subsampling process of 3d laser scanning data for robust registration

## Data Preprocessing and Subsampling

The process of segmentation removes all unwanted data, but it is very important that both the data sets have similar data densities to avoid biases of the registration towards denser parts of data. Hence, the authors use a two-step process to subsample both the 3D laser scanning data sets to maintain similar data densities across the point clouds. The two-step process firstly subsamples both the 3D laser scanning data sets to maintain uniform spacing between points. This process will subsample the 3D laser scanning data sets by maintaining a similar number of neighbors around a point in denser areas and not altering points in parts having sparser data points. The next step is to interpolate the sparser parts of the point cloud data and increase its density to the same level as other parts keeping similar densities across point clouds. The authors conducted these two steps using the subsample tool available in CloudCompare *(13)*. Figure 3 (c & d) shows an example of a subsampled 3D laser scanning data sets collected in 2015 and 2016 having uniformly distributed points. After the segmentation and subsampling process, the robust registration approach detailed in the following section will align 3D data sets from different years for change detection.

## Robust Registration Algorithm

3D laser scanning data collected at different times enable spatial change detection of the bridge structure. Examples of these spatial changes include overall deviation of the bridge structure (rigid body motion), deviations of individual bridge elements, and deformation of the individual bridge elements. However, the first step is to identify the rigid body motion of the bridge structure, which can help in identifying the other spatial changes. Such rigid body motion of the bridge can be identified by accurately registering 3D laser scanning data collected at different times. The collected 3D laser scanning data sets contain several common features and other additionally captured features of objects around the bridge structure. There may be cases that one point cloud data may contain features that might be missing in other point cloud data set. If a registration process is implemented during such case, the registration result will be biased toward the additional features, which is missing in one of the captured point cloud data. Hence, the reliable registration approach must segment both the point cloud data sets so that both contain exact same environment and bridge features that improve the quality of the registration results. The following paragraph details the process of segmenting both the point cloud data sets to contain exact same environment and bridge features that utilize a robust plane fitting approach to identify unchanged data points between the collected data sets. Failure to accurately segment

the point cloud data sets will affect the plane fitting step that eventually affects the overall robust registration approach.

The segmented and subsampled 3D laser scanning data sets contain several common points between them. Manually identifying unchanged points between two data sets is tedious. Hence, the authors developed an automatic method that utilizes all the points in the point clouds to automatically and accurately identify unchanged parts between the two compared 3D laser scanning data sets (e.g., data collected in 2015 and 2016). First, the algorithm utilizes a robust plane fitting approach to fit a plane between all the points found in both the old (Points $o_1$, $o_2$, $o_3$… $o_n$) and new (Points $n_1$, $n_2$, $n_3$… $n_n$) 3D laser scanning data. The robust plane fitting approach utilizes the Principle Component Analysis (PCA), which minimizes the perpendicular distances between the points and the fitted plane *(23)*. Using such plane fitting approach, the authors robustly fit one plane between the points from the old ($P_O$) data collected in 2015 and an another plane between the points from the new ($P_n$) data collected in 2016. The output of such plane fitting process is the center of the plane and the orthogonal distances between the fitted plane and all the points. However, if either of the point clouds contains data points that capture objects in one of the point cloud data and is not captured in the other point cloud, the robust plane fitting approach may generate a plane biased towards such additionally captured data parts that are missing in one of the compared point clouds. That plane would not well represent the overall trends of data points in the data set that have parts of data missing, making the comparison of two point clouds not on the same basis. In order to avoid such issues, the authors only keep data points that are visible in both of the compared point clouds. That process segments both point clouds such that they share the exact same boundary, which contains the captured bridge and environmental features. Such segmentation is important so that a robustly fitted plane from one point cloud can be a good basis to assess the changes of the other data set. These two data sets capturing similar parts of the scene should have similar trends represented by a robustly fitted plane for analyzing differences between 2015 and 2016 point clouds which contain several spatial changes. The authors utilize the cross-section segmentation tool found in CouldCompare *(13)*, which utilizes a bounding box to edit and segment 3D laser scanning data sets. The cross-section segmentation process consists of maintaining the exact same size of the bounding box, which eventually helps in maintaining similar features between the two 3D laser scanning data sets. This step will aid in improving the overall quality of the robust registration algorithm. Figure 3 shows an example of a segmented 3D laser scanning data of a bridge structure collected in 2015 and 2016 respectively. The authors performed the segmentation process such that both the 3D laser scanning data sets contain the similar parts of the scene.

Since both the 3D laser scanning data sets are roughly registered and in the same global coordinate system, the algorithm then calculates the orthogonal distances between the data points in the old point cloud collected in 2015 and the old plane that is derived from old point cloud ($Do_1$, $Do_2$, $Do_3$ … $Do_n$ hereafter). Similarly, the algorithm calculates the distances between the data points in the new point cloud collected in 2016 and the old plane that is derived from old point cloud ($Dn_1$, $Dn_2$, $Dn_3$ … $Dn_n$ hereafter). Such process of calculating the orthogonal distance between the old and new points with the same old plane derived from old point cloud will help to identify unchanged points among the old and new point clouds. The authors now calculate the distance between the two fitted planes $P_O$ and $P_n$, say $D_{on.}$ The next step in the robust registration algorithm is to associate every point in the old point cloud (2015 point cloud) to each point in the new point cloud (2016 point cloud) using the nearest neighbor approach. The nearest neighbor approach associates each individual old points to each new points based on the smallest distance between them. The rough registration approach brings both the data sets into a

single global coordinate and the nearest neighbor approach associates each point in the old point cloud (2015 point cloud) to its corresponding closest point in the new point cloud (2016 point cloud). Assuming that $o_1$ is the nearest neighbor to $n_1$, $o_2$ is the nearest neighbor to $n_2$ and so on for all other points.

Now, the algorithm calculates the difference between orthogonal distances of the all the associated nearest neighbors such as $D_{O1} - D_{n1}$, $D_{O2} - D_{n2}$, etc. If one of the calculated orthogonal difference is smaller than $D_{on}$,, then the algorithm identifies those corresponding points as unchanged. For instance, if $D_{O1} - D_{n1} < D_{on}$, the algorithm identifies that the corresponding point $D_{O1}$ and $D_{n1}$ remain unchanged between old and new point cloud data. Hence, the algorithm identifies all corresponding old and new points that have the difference in the orthogonal distances smaller than $D_{on}$. This process now eliminates all the changed points and extracts only those unchanged points that are utilized for automatic registration between both the collected 3D laser scanning data sets. The algorithm now utilizes an Iterative Closest Point (ICP) registration *(14)* to register unchanged old and new points and determine its corresponding transformation matrix. This transformation matrix provides the translation and rotation values required to accurately align the new points to their corresponding old points and eventually to register the entire old and new 3D laser scanning data from which those points were extracted. Therefore, this process determines the transformation matrix between the unchanged old and new points and algorithm uses this transformation matrix to register both the collected 3D laser scanning data sets required for reliable geometric change detection of bridges.

## VALIDATION

To validate the developed robust registration approach, the authors compared its registration results with the traditional registration approach, which relies on matching features points between two sets of 3D laser scanning data. The comparison process relies on comparing the transformation matrix generated by the robust registration approach with that of the transformation matrix generated by the traditional registration approach. A transformation matrix consists of translation parameters that consist of displacement along x, y, and z coordinates and rotation parameters that consists of rotation along α (rotation around the x-axis), β (rotation around the y-axis), and γ (rotation around the z-axis) that helps to register the 2015 3D laser scanning data with the 2016 3D laser scanning data *(24)*. The final output of the robust registration approach is the transformation matrix, which is compared with the registration results of the traditional registration approach. The following section provides details about generating the transformation matrix using the traditional registration approach.

The authors executed a registration approach that iteratively selects unchanged feature points between the two data sets. The improved manual feature point selection approach utilizes manually selected feature points on the bridge and its surrounding common in the 3D laser scanning data collected in 2015 (old data) and 2016 (new data) respectively. Specifically, the authors selected several feature points on a nearby culvert and few feature points on the part of the bridge structure. The process of manually selecting feature points involves selecting few common feature points between the old and the new 3D laser scanning data. For instance, the authors have selected 11 common feature points (bridge & environment) between the two data sets. Then the authors select three points each from the previously selected set of 11 common feature points such that the triangle formed by connecting the three feature points in the old data is similar to the triangle formed by the feature points in the new data. Here, the similarity between the two triangles can be obtained by maintaining the equal length of the sides of the triangle. Now the authors perform the registration between the old and the new 3D laser scanning data using these three selected feature points to obtain the transformation matrix. After this

registration step, the authors calculate the change in the distance between the remaining 8 feature points from the old 3D laser scanning data with their corresponding 8 feature points from the new 3D laser scanning data. Such calculation will provide information about those features points that have undergone significant changes after the first registration step.

Next, the authors identify the least changing common feature point between the old and the new 3D laser scanning data. After identifying the least changing feature point, the authors again perform the registration between the original old and new 3D laser scanning data using the previously identified 3 common feature point and the least changing common feature point. This registration step generates another transformation matrix. The authors calculate the difference in the new transformation matrix (4 feature point registration) and the old transformation matrix (3 feature point registration) and identify if any of the translation (translation along x, y or z coordinate directions) value difference is above a certain threshold. The authors set 30 cm as value for the threshold. Here, the authors ignored the rotation values from the transformation matrix, as these rotation values are significantly smaller. If the difference between both the transformation matrices is above the threshold, then the authors continue the registration process by calculating the change in the distance of the remaining 7 feature points from the old scan with their corresponding 7 feature points from the new scan to identify the least changed feature point. In the next step, the authors again perform another registration between the original 3D laser scanning data sets using the 4 previously selected feature points and the new identified least changed feature point to obtain another transformation matrix. If the difference between the new transformation matrix and the previous transformation matrix is below the threshold value, then the authors end this registration process and treat the new transformation matrix as final. If the difference between the new transformation matrix and the previous transformation matrix is above the threshold value, then the authors continue the registration process by again identifying another least changed feature point among the remaining common feature points. The above described registration using manual feature point selection approach iteratively identifies least changing feature points by gradually registering both the old and the new 3D laser scanning data. This iterative registration approach can be utilized in cases of a bridge data having no similar environmental feature points to perform the robust registration approach. The authors validated the developed robust registration approach using a case study of a highway bridge structure detailed in the following section.

## CASE STUDY

First, the authors segmented, subsampled, and roughly aligned both the 2015 and 2016 3D laser scanning data sets (Figure 4). Now the authors applied the robust registration algorithm to accurately register both the 2015 and 2016 3D laser scanning data (Figure 4 (c)). Figure 4 shows the obtained transformation matrix (Table 1), which contain the translation and rotation parameters to robustly register both the 3D laser scanning data sets. These robustly registered 3D laser scanning data sets to aid in reliable geometric change detection of bridges for performing accurate condition diagnosis. Therefore, the changes detected from such robustly registered 3D laser scanning data sets reflect the actual geometric changes of a bridge structure rather reflecting changes due to registration errors between the two data sets. Now the authors implement the improved feature point registration approach to manually register both the 2015 and 2016 3D laser scanning data. To implement the improved traditional registration approach, the authors initially selected 11 feature points and then identified that there is no significant change in the obtained transformation matrix when using 6 least changed commonly identified feature points.

Table 1 shows the final transformation matrix using the 6 identified feature points, and its comparison with the transformation matrix generate using robust registration approach.

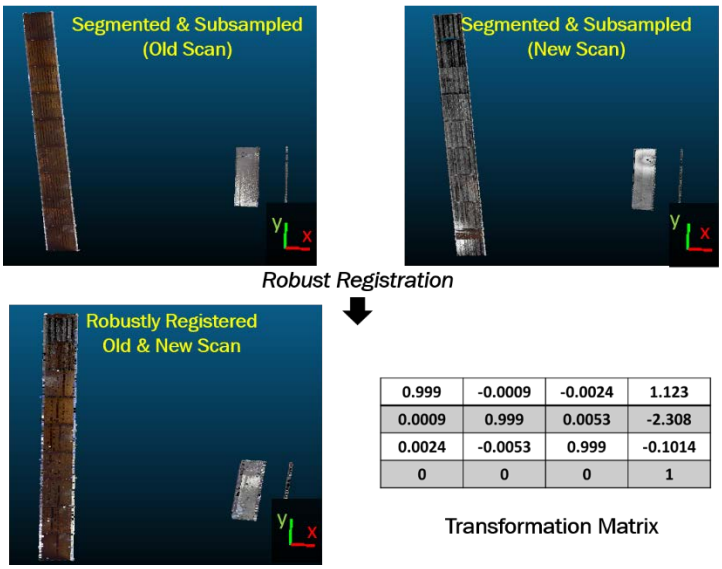


**Figure 4** Segmented, subsampled and robustly registered 3D laser scanning data of the highway bridge (z-axis along elevation).

**Table 1** Comparison of the registration results (Robust Registration vs. Manual Registration)

| REGISTRATION TYPE | TRANSLATION VALUES | | | ROTATION VALUES | | |
|---|---|---|---|---|---|---|
| | *X* | *Y* | *Z* | *α* | *β* | *γ* |
| **Robust Registration Approach** | 1.123 | -2.308 | -0.1014 | 0.0053 | 0.0024 | -0.0009 |
| **Registration using Improved Manual Feature Point Selection** | 1.208 | -2.743 | -0.0812 | 0.0078 | 0.0026 | -0.00018 |

The comparison results show that the developed robust registration approach is qualitatively same but slight vary quantitatively from the registration results using manual feature point selection. This means that both the registration approaches output results that have the same direction of translation and the direction of rotation along all the coordinate axes. Additionally, the quantitative difference between all the registration results is very small and does not significantly affect the results of the geometric changes detected between the collected 3D laser scanning data sets. This comparison study validates the robust nature of the developed robust registration approach and its substantial advantage for performing automatic and reliable geometric change detection of the bridges using 3D laser scanning data over other traditional approaches.

## CONCLUSION AND FUTURE RESEARCH

This paper presented a novel robust registration approach that automatically detects unchanged common points between two sets of 3D laser scanning data and accurately registers them into one global coordinate. The developed approach first segmented redundant data and subsampled both the 3D laser scanning data sets. Then a robust registration algorithm automatically extracted unchanged points on both the bridge and its surrounding environment to perform a point-to-point registration. Such process does not require any manual intervention or

the tedious process of manually selecting unchanged points. The authors applied the developed registration approach on highway pre-stressed Concrete Bridge and validated the registration results by comparing it with the traditional manual feature point selection registration approach. The developed robust registration algorithm utilizes several environment feature points that surround the bridge structure. However, in some cases, these environment feature points undergo higher spatial changes than the bridge structure.

In the future, the authors plan to study the effect of spatial changed environmental feature points on the registration results. The authors plan to use the surveying data collected using a Total Station sensor to establish several control point network using the environmental features around the bridge structure. These ground control points can aid in understanding the spatial changes of these environmental features that can be incorporated in registering two sets of 3D laser scanning data collected at different times. Hence, using both the data generated by the 3D laser scanners and the Total Station sensor can help in developing more robust registration approach that is not affected by the spatial changes of the environment surrounding a bridge structure.

In addition to developing reliable registration techniques, the author plans to develop a 3D imagery data-driven bridge deterioration monitoring and decision making framework that evaluates the health of a bridge structure becoming an integrated part of the bridge management system for conducting reliable risk asset management. Several researchers developed bridge data management systems that manages the sensor and bridge metadata for damage detection and long-term monitoring of bridge structures *(25)*. Therefore, the author plans to develop a 3D imagery data management system that collects and manages timely imagery data of several bridge structures for aiding detailed geometric analysis, condition assessment tracking and spatiotemporal change monitoring.

## ACKNOWLEDGMENTS

This material is based upon work supported by National Science Foundation (NSF) under Grant No. 1443069 and Grant No. 1454654. NSF's support is gratefully acknowledged. The authors would like to thanks, Jimmy Camp and Ryan Jones from Maricopa DOT for giving us permission to collect laser scanning data and providing the design drawings of the bridge.

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