# AUTOMATIC AWARENESS OF TRAFFIC SIGN CONDITION CHANGES USING MULTI-TEMPORAL SENSING DATA

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## ABSTRACT

Traffic signs are one of the most important assets for transportation systems; they provide vital guidance to road users and ensure roadway safety. Transportation agencies need to perform routine inspection and timely maintenance to keep traffic signs at good service condition. Traditionally, transportation agencies conduct traffic sign condition assessment manually. These methods can be extremely time-consuming and costly. More importantly, using the manual records, it is very challenging for transportation agencies to monitor the temporal condition changes of traffic signs, and there lacks detailed information to understand the insights of frequency, trend, and possible causes of these condition changes. There is a need for a reliable and efficient method to identify and quantify the temporal condition changes of traffic signs, so that an optimized maintenance plan can be effectively carried out. This paper proposes a framework for automatic awareness of traffic sign condition changes using multi-temporal sensing data. This framework can not only identify the damaged traffic signs for immediate treatment, but can also provide insights for understanding the progression of subtle condition changes before traffic signs are severely damaged. A prototype algorithm for identifying and quantifying bent traffic sign using mobile LiDAR is developed to substantiate the framework and demonstrate its feasibility. Experimental test was conducted on Interstate 85 within the state of Georgia to evaluate the performance of the developed algorithm and the proposed framework. The proposed framework shows promising results in identifying bent traffic signs and quantifying the subtle changes of the bending angles using multi-temporal sensing data. By incorporating additional traffic sign condition identification algorithms, the proposed framework can provide a reliable and efficient means for transportation agencies to implement their traffic sign maintenance system through automatic condition change awareness.

## INTRODUCTION

Traffic signs are one of the most important assets for transportation systems; they provide vital guidance to road users regarding traffic regulation, warnings, destination information, and temporary road condition information. However, the condition of traffic signs constantly deteriorate due to many reasons, e.g. aging, environmental, vandalism, etc., which can dramatically degrade their visibility and eligibility *(1)*. It is critical for transportation agencies to conduct routine inspection and timely maintenance to keep traffic signs in good service conditions. There are two inherent needs from transportation agencies in traffic sign condition inspection; they are 1) to identify the locations of damaged signs, so that a timely treatment can be performed, and 2) to monitor the temporal condition changes of the traffic signs, so that optimized traffic sign maintenance strategies can be performed by understanding the progression of condition changes of traffic signs before they are severely damaged. Traditionally, transportation agencies conduct manual traffic sign condition inspection, using either windshield or detailed field survey. These manual methods can be extremely time-consuming and costly. More importantly, using the manual records, it is very challenging for transportation agencies to monitor the temporal condition changes of traffic signs before they are severely damaged, and there lacks detailed information to understand frequency, trend, and possible causes of the condition changes.

With advances in sensing technologies, several automatic methods have been developed to identify damaged traffic sign or traffic signs with poor conditions. VISUAL Inspection of Sign and panEL (VISUALISE) system is developed by Gonzales, et al. *(6)* to automatically assess retroreflectivity condition using calibrated correlation between image intensity and retroreflectivity. A Multi-scale Sign Image Matching (M-SIM) method was developed by Tsai et al. *(3)* to automatically identify the missing, tilt and blocked traffic signs using camera calibration and scale-invariant feature transform (SIFT). Although some of these automatic methods report appealing results and can potentially improve the current practice for identifying damaged traffic signs, none of these methods are designed to support transportation agencies' need for temporal monitoring of traffic sign condition changes. Hence, this paper proposes a comprehensive framework for automatic traffic sign condition change awareness using multi-temporal sensing data. This framework is targeted at not only automatically identifying traffic signs that are damaged and require immediate treatment, but also targeted at quantifying the subtle temporal changes of traffic signs before they are severely damaged. This framework can help transportation agencies to better understand the progression of the traffic sign condition changes, and eventually to facilitate optimized traffic sign maintenance strategies. The proposed framework includes four key components, including: 1) traffic sign data acquisition, 2) traffic sign condition identification, 3) multi-temporal sensing data merging, and 4) traffic sign condition change quantification.

The proposed framework can adapt existing and forthcoming algorithms for identifying traffic sign conditions. A prototype bent traffic sign identification and quantification algorithm using mobile light ranging and detection (LiDAR) is developed to substantiate the proposed framework and demonstrate its feasibility. The actual multi-year data is collected on Interstate 85 within the state of Georgia to evaluate the performance of the developed algorithm and the proposed framework.

This paper is organized as follows. The first section identifies the research need and objective. The second section presents typical traffic sign damages or poor conditions that are concerned by transportation agencies. The third section presents the proposed framework. The fourth section presents a prototype algorithm for identifying and quantifying bent traffic signs using mobile LiDAR. The fifth section presents the experimental test conducted on I-85 to demonstrate the feasibility of the proposed framework. Finally, the conclusions and recommendations for future research are presented.

## TYPICAL TRAFFIC SIGN DAMAGES AND POOR CONDITOINS

Damaged traffic signs or traffic sign with poor condition can no long supply adequate visibility and/or eligibility *(2, 4)*. Transportation agencies define damaged traffic signs and poor conditions differently based on maintenance requirement, causes, severity, etc. The following for types are commonly used by transportation agencies as shown in FIGURE 1.


**FIGURE 1 Typical traffic sign damages and poor conditions**

- Bent signs: bent traffic signs refer to the traffic signs whose surfaces are distorted due to environmental issues, inappropriate mounting, material aging, etc. Some of the severely bent traffic signs require immediate replacement as the intended information of the traffic signs can be invisible or ineligible due to the bent;
- Vandalized signs: vandalized signs refer to the traffic signs that are damages by vandalization, e.g. paint ball, sticker, graffiti, etc. Vandalized signs should be repaired or replaces due to the destruction of the intended information;
- Obstructed signs: obstructed signs refer to the traffic signs that are completely or partially blocked by obstructions, e.g. vegetation, facility pole, etc. The obstruction should be removed in timely measure to maintain the visibility of the traffic signs;

- Signs with poor retroreflectivity: poor retroreflectivity condition refer to the night time visibility of the traffic signs. The minimum requirement of the retroreflectivity is required by the latest manual of uniform traffic control devices (MUTCD) *(2, 5)*. Traffic signs with poor retroreflectivity require timely replacement to provide adequate nighttime visibility.

Transportation agencies routinely inspect the abovementioned traffic sign conditions and perform timely treatment on traffic signs that are severely damaged. Constraint by agencies' stringent funding availability, some of traffic sign conditions may not trigger immediate treatment, but still require continuous monitoring. However, the current manual inspection results cannot provide quantitative measurement for tracking the temporal condition changes. This paper proposes a framework that can not only identify traffic signs that are severely damages for immediate treatment, but can also provide temporal monitoring of the condition changes, so that optimized traffic sign maintenance strategies can be performed by understanding the progression of these changes of traffic signs before they are severely damaged.

## PROPOSED FRAMEWORK

The objective of the proposed framework is to serve the two inherent needs from transportation agencies in traffic sign condition inspection: 1) to identify the locations of damaged signs and 2) to monitor the temporal condition changes of the traffic signs. The proposed framework consists of four key components, including traffic sign data acquisition, sensing-based traffic sign condition identification, multi-temporal sensing data merging, and traffic sign condition change quantification. FIGURE 2 shows the overall flowchart of the proposed framework.

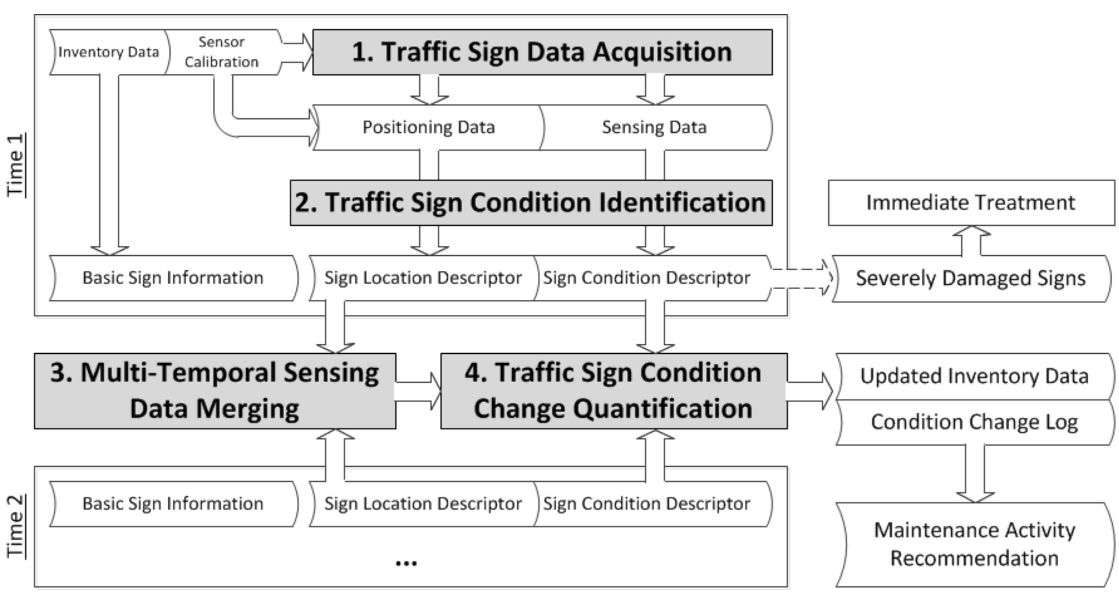



**FIGURE 2 Flowchart of the proposed framework for automatic traffic sign condition change awareness**

Component 1: Traffic Sign Data Acquisition: At each time of data acquisition, e.g. annually, both the new sensing data, e.g. video log images, LiDAR point cloud, global navigation satellite system (GNSS) data, etc., and the existing inventory data are collected and integrated using geo-references, so that each inventoried traffic sign record will be associated with its corresponding video log image and LiDAR point cloud. FIGURE 3 shows an example of the inventoried sign record that is associated with the new sensing data. The video log images and the traffic sign-associated LiDAR point clouds retrieved from the sensing data. A unique location descriptor is assigned to each inventoried sign record, e.g. GPS coordinates, etc.

| Field | Value |
|---|---|
| ID | 5354.00000 |
| Longitude | -84.3916535515 |
| Latitude | 33.7808477237 |
| Elevation | 251.0272604479 |
| MUTCD | W4-2 |
| Overhead Type | Ground Mount - 0.00000 |

**FIGURE 3 Example of the integration of inventory record and sensing data**

Component 2: Traffic Sign Condition Identification: For each inventoried sign record, the corresponding sensing data, i.e. video log image, LiDAR point cloud, etc., is processed using different condition identification algorithms. A detailed traffic sign condition descriptor is created to store the fundamental condition information for each traffic sign record, e.g. retroreflectivity, surface facing, etc. FIGURE 4 shows two examples of the sign condition descriptor for different sign conditions for a bent interstate sign with 100 degree bending angle, and a vandalized merge sign with 5% coverage. Both existing and forthcoming algorithms can be integrated in this component to fulfill the attributes of the sign condition descriptor. Transportation agencies can define their criteria for determining damaged signs for immediate treatment. For example, if all the traffic signs with and bending angle greater than 15° need be to be repaired, the interstate sign with a bending angle of 100° will require immediate flattening repair. In the subsequent section, a prototype algorithm for bent sign identification and measurement is presented to substantiate this concept.


**FIGURE 4 Examples of the condition descriptor for different traffic sign conditions**

Component 3: Multi-Temporal Sensing Data Merging: For the sensing data acquired at different time, the spatial correlation is established by registering the corresponding positioning data. According to the availability of the positioning data, different registration method can be employed, e.g. LiDAR registration *(10, 11)*, image-LiDAR registration *(12)*, or image-based registration *(13, 14)*. Since each traffic sign record incorporates the derived traffic sign condition information from the previous step, the corresponding records acquired at different times can be spatially registered and compared. FIGURE 5 shows an example of the registration result using LiDAR point clouds from two different times. It can be observed that after the data merging, the corresponding traffic sign records from the consecutive years can be associated.

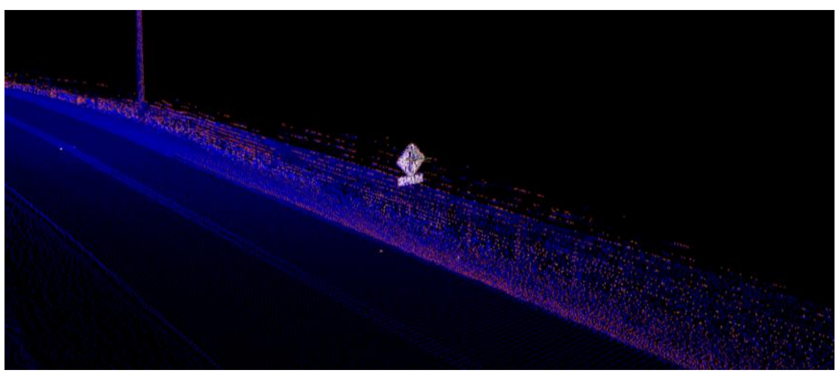


**FIGURE 5 Example of multi-temporal sensing data merging using LiDAR point cloud (Time 1- blue, Time 2 – red; Overlapped traffic sign – white)**

Component 4: Traffic Sign Condition Change Quantification: Once the corresponding traffic sign records are associated, the condition changes can be quantified by comparing the corresponding attributes of the sign condition descriptors. For example, the deterioration of the retroreflectivity condition can be monitored to predict the expected service life for each individual traffic sign, so that a sheeting replacement prioritization can be performed. In the subsequent section, a prototype algorithm is developed to quantify the degree of sign bent to demonstrate the concept of sign condition change quantification. The quantified condition changes can be automatically updated to the condition change logs and the updated inventory data will be recorded, so as to support transportation agencies' maintenance activity recommendation and prioritization.

## PROTOTYPE ALGORITHM FOR BENT SIGN EVALUATION

A prototype algorithm for automatically identifying bent traffic signs and measure the bending angles using LiDAR point cloud data is developed in this paper to substantiate the key components of the proposed framework. FIGURE 6 shows the flowchart of the developed algorithm, each step of which is corresponded to the proposed framework in FIGURE 2. As the Components 1 and 3 have described in previous section, this section focuses the Components 2 and 4, the octree-based coplanar clustering and the bending change comparison respectively.

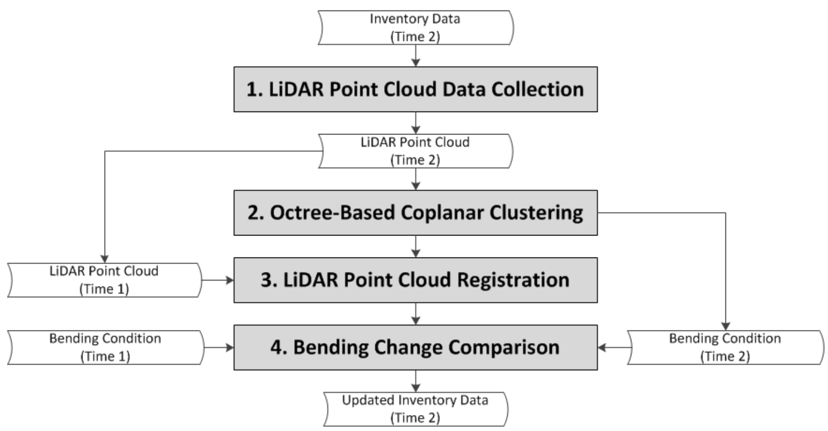



**FIGURE 6 Flowchart of the proposed algorithm for bent traffic sign evaluation**

### Octree-Based Coplanar Clustering

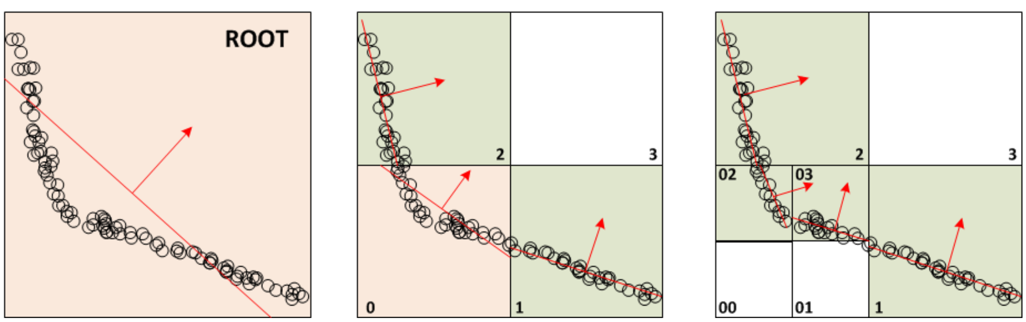
A coplanar clustering algorithm using octree-based split and merge method *(8)* is introduced to determine whether the traffic sign is bent, and to compute the bending angles if bent. The split process of the algorithm is to recursively split the LiDAR point cloud that is associated with a traffic sign, until each node of the octree only contains points that satisfy the coplanar criterion. The merge process of the algorithm is the applied to combine the neighboring nodes if the points in the combined node still satisfy the coplanar criterion. The merging process will be exhaustively conducted until no neighboring nodes can be merged without violating the coplanar criterion. If there is only one node remains (i.e. one cluster), then the traffic sign is not bent. Otherwise, a bent traffic sign is identified, and the number of nodes (i.e. clusters) indicates the number of facets of the bent traffic sign. The angle between the two largest nodes will be computed as the bending angle of the traffic sign.

The coplanar criterion is determined using the principle component analysis (PCA) *(9)*. The following equations are constructed for PCA computation for the optimal normal of the given data, i.e. points within a node. The solution is obtained from the three eigenvectors. The eigenvectors represent the three axes of the points, while the eigenvalues denote the square sum of points deviating along the corresponding axis. Therefore, the minimum eigenvalue represents the variation along the normal direction of the best estimated plane using the points within each node.

$$C = \frac{1}{k}\sum_{i=1}^{k}(\boldsymbol{p}_i - \overline{\boldsymbol{p}}) \cdot (\boldsymbol{p}_i - \overline{\boldsymbol{p}})^T, \qquad C \cdot \vec{v}_j = \lambda_j \cdot \vec{v}_j, j \in \{0,1,2\}$$

where $k$ is the number of points in the point cloud $\boldsymbol{p_i}$, $\overline{\boldsymbol{p}}$ is the centroid of the cluster, $\lambda_j$ is the j-th eigenvalue of the covariance matrix $C$ and $\vec{v}_j$ is the j-th eigenvector. Coplanar points should result in very small variation along the normal direction of the estimated plan. Therefore, the coplanar criterion is defined as $\min(\lambda_j) \leq \Delta$). The selection of the threshold $\Delta$ is determined by the systematic range measurement error of the LiDAR sensor.

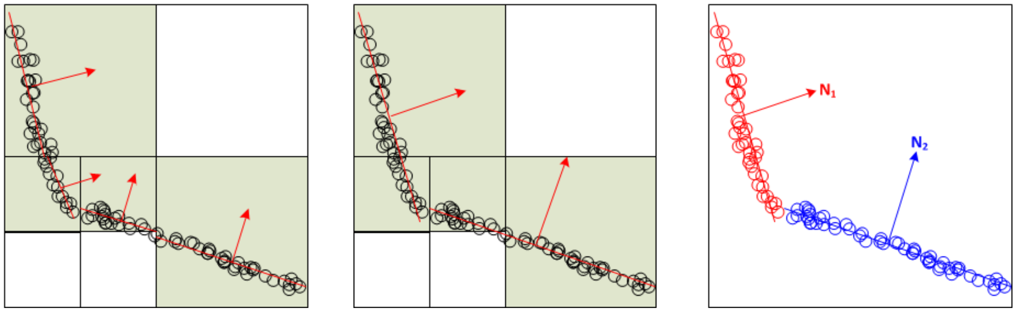
FIGURE 7 shows an illustration of the split process using a 2-D example. FIGURE 7(a) shows the space contains all the traffic sign associated LiDAR points, as the root node. Since the coplanar criterion is not satisfied, the space is split into eight sub-spaces (only four shown in FIGURE 7(b)). The points set in node 1 and 2 pass the coplanar criterion, so no further split is required. The points set in node 0 will be further split into eight sub-spaces, as shown in FIGURE 7(c). Since the points set in all the nodes pass the coplanar criterion, no further split is required.




(a) (b) (c)

**FIGURE 7 Split process of the proposed algorithm**

FIGURE 8 shows an illustration of the merge processing. As shown in FIGURE 8(a), the points in neighboring nodes can share a similar normal direction, which indicates that these points should be merged into the same cluster. Therefore, for each node, the coplanar test is conducted by including the points from one of the neighboring nodes. If the coplanar criterion is satisfied, the two nodes are merged into one as shown in FIGURE 8(b). The merging process is exhaustively conducted for all the nodes until no further merging can be conducted. FIGURE 8(c) shows the results of the clustering. Two nodes (i.e. two clusters) are identified in this point cloud, which means a bent traffic sign is identified. As shown in FIGURE 8(c), by computing the angle among different normal vectors from each facet, the bending angle is determined for the identified bent traffic sign, i.e. $\langle \boldsymbol{N_1}, \boldsymbol{N_2} \rangle$ .




(a) (b) (c)

**FIGURE 8 Merge process of the proposed algorithm**

**Bending Change Comparison**

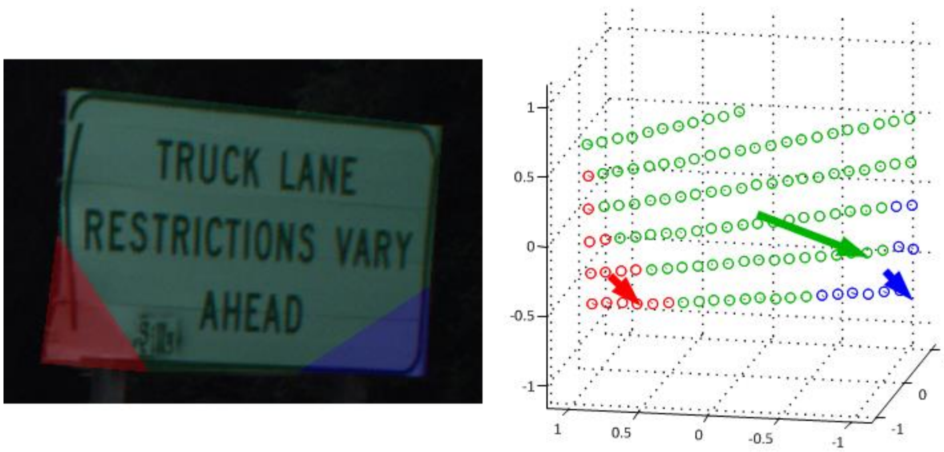
With the detailed information derived from the developed algorithm, transportation agencies can not only clearly identify the bent traffic signs, but can also compare the condition with previous data and quantify the changes of the bending (i.e. angle increases – more severe bending, facet increases – more severe bending and rolling, etc.). This prototype algorithm uses bent traffic signs as an example to demonstrate the feasibility of the proposed framework.

## EXPEREMENTAL TEST

The objective of the experimental test is to evaluate the performance of the developed prototype algorithm and the overall feasibility of the proposed framework for traffic sign condition change awareness. The data on I-85 within the state of Georgia is collected in FY2013 to conduct the experimental test, which consists of more than 115 thousand frames of video log images and more than 91million LiDAR points.

To evaluate the performance of the develop prototype algorithm, the ground truth was established by manually review of the sensing data collected in FY2013. Among all of the 2505 traffic signs inventoried, 10 bent traffic signs are identified. FIGURE 9(a) shows examples of the identified bent signs. The automatic traffic sign detection algorithm developed by Ai and Tsai *(7)* was applied first to extract the LiDAR point clouds that are associated with traffic signs. The developed algorithm was then applied to each of the LiDAR point clouds to identify the bending changes and measure the degree of bending. All of the 10 bent traffic signs were correctly identified, while the bending angles were computed. FIGURE 9(b) shows a result of the identified bent signs with the perspective view and the computed normal directions.


(a)




(b)

**FIGURE 9 Results of the proposed algorithm**

To demonstrate the feasibility of the proposed framework, an additional data collection in FY2014 was conducted to demonstrate the bending condition changes in the consecutive years. By registering the sensing data in FY2013 and FY2014 and comparing the bent sign identification results derived from the developed algorithm, the following changes were observed:

- 8 out of the 10 bent traffic signs in FY2013 was repaired/replaced by Georgia Department of Transportation;

- 3 new bent traffic signs were identified in FY2014 which requires incoming maintenance;
- 2 out of the 10 bent traffic signs in FY2013 remained unrepaired. A progression of the bending angle is identified using the proposed framework in one of the two bent signs. FIGURE 10 shows the comparison of the progression in bending angles. It can observed from the video log images in FIGURE 10 (a) that the top part of the speed limited sign in has a narrow bent, and the bent becomes more severe in the later year, i.e. FY 2014. FIGURE 10(b) shows the point cloud projected along the side of the speed limit sign to illustrate the progression of the bending angle. In FY2013 the bending angle $\alpha$ is 26°, while the bending angle $\alpha$ increases to 46° in FY2014.

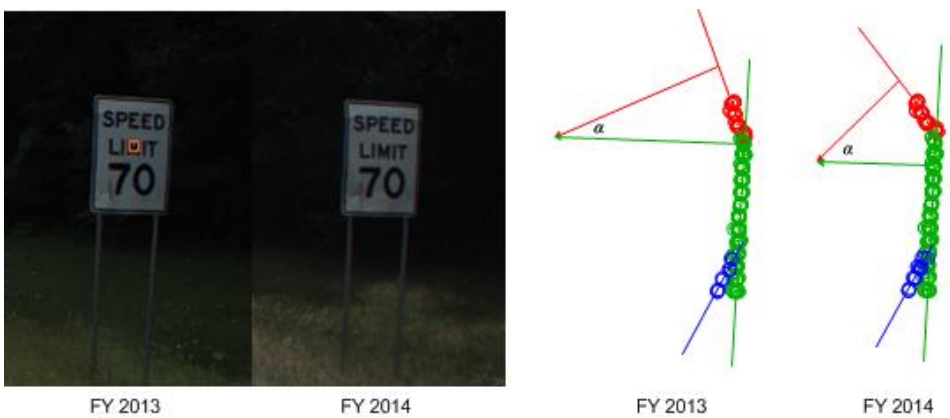



**FIGURE 10 Comparison results between FY2013 and FY2014**

The results using the sensing data collection in FY2013 and FY2014 clearly demonstrate that by integrating the developed algorithm, the proposed framework can conveniently identify the bending changes using mobile LiDAR data. By integrating algorithms for identifying other sign condition changes, the proposed framework can more comprehensively support transportation agencies with an informed traffic sign maintenance strategy by synthesizing all the identified condition changes and prioritize the maintenance activities accordingly.

## CONCLUSIONS AND RECOMMENDATIONS

This paper proposes a comprehensive framework for automatic traffic sign condition change awareness using multi-temporal sensing data. This framework is targeted at not only automatically identifying traffic signs that are severely damaged and require immediate treatment, but also targeted at quantifying the subtle temporal changes of traffic signs before they are severely damaged. This framework can help transportation agencies to better monitor the progression of the traffic sign condition changes, understand the frequency, trend and possible causes of the condition changes, and eventually to facilitate optimized traffic sign maintenance strategies.

While the proposed framework is general enough to adapt different traffic sign condition or traffic sign damage identification algorithms, a prototype bent sign identification algorithm is developed in this paper to substantiate the proposed framework and demonstrate the feasibility of the proposed multi-temporal condition change awareness. An experimental test using the sensing data collection on I-85 was conducted to validate the developed algorithm and the proposed framework. Comparing with the manual ground truth, all of 10 bent traffic signs from FY2013 data are successfully identified by the developed algorithm.  By comparing the results of the identified bent traffic signs from FY2013 and FY2014, the changes of the bent signs are reliably monitored by comparing the conditions derived from the multi-temporal sensing data. The locations of repaired bent signs, newly bent signs and deteriorated bent signs are accurately retrieved. Such comprehensive information provides transportation agencies insights for understanding the frequency, deterioration trend, and possible causes of the changes, which can lead to optimized maintenance strategies.

For future improvement and development of the framework, the following recommendations are provided: 1) The accuracy of the bending angle measurement should be further validated; 2) Larger datasets with diverse traffic sign conditions and from different sensor models and configurations should be further evaluated; and 3) Additional automatic traffic sign condition identification algorithms should be further incorporated in the proposed framework for further validation.

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