FILTERING OF BRIDGE-SLAB BENDING EFFECT IN TERRESTRIAL LASER SCANNING

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KEY WORDS: Terrestrial laser scanning, Bridge model, Slab-bending, Noise filtering

ABSTRACT: In this work, 3D measurement, such as terrestrial laser scanning, is applied for advanced infrastructure management and building information modeling (BIM). Although terrestrial laser scanning can acquire point cloud data for BIM, 3D measurement using high-precision laser scanning is affected by slab bending with active loading, such as vehicle movements on a bridge. Thus, stripy noises occur in acquired point clouds. To remove the stripy noises for precise 3D bridge modeling, we propose two methodologies: multiple data subtraction and noise pattern estimation. Through experiments, we confirmed that our algorithms can automatically cancel the slab-bending effect of a bridge in laser scanning works.

1. INTRODUCTION

In recent research, 3D measurement, such as terrestrial laser scanning, has been applied for advanced infrastructure management and building information modeling (BIM) (Bosché et al. 2015). Although terrestrial laser scanning can acquire point cloud data for BIM, 3D measurement using high-precision laser scanning is affected by slab bending with active loading such as vehicle movements on a bridge. Figure 1 shows an example of stripy noises present in point clouds.

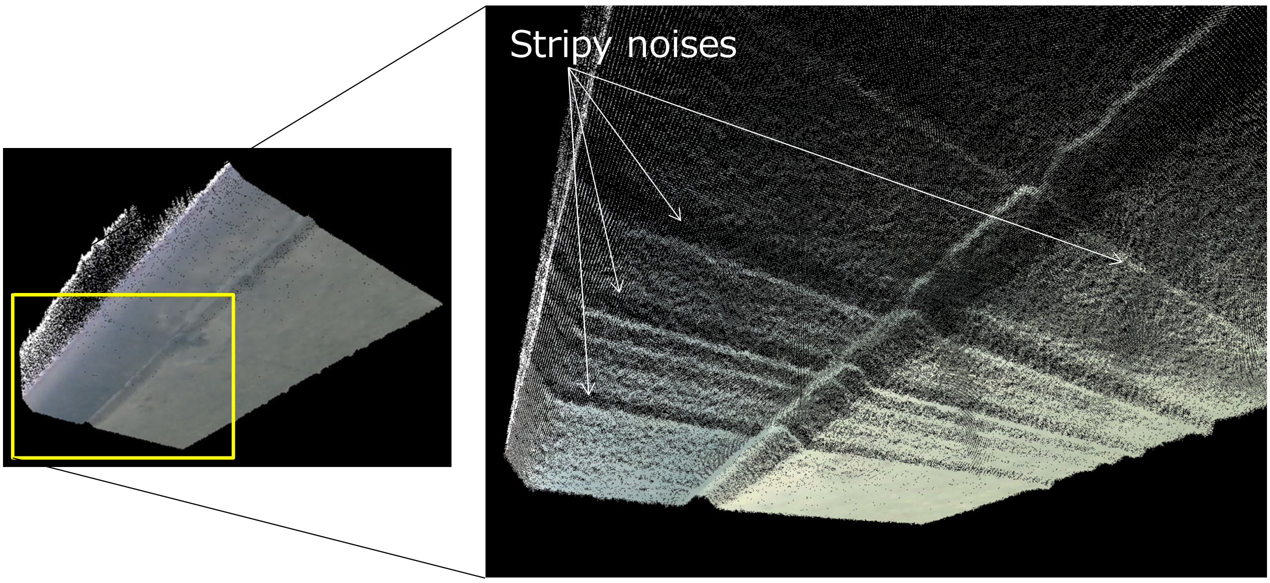

Figure 1. Example of stripy noises

When we remove noise from point clouds, we can apply a plane estimation approach with random sample consensus (RANSAC) (Fischler and Bolles 1981). Although RANSAC is a useful algorithm for outlier filtering, it requires a threshold value to remove outliers from point clouds. In contrast, the least median of squares (LMedS) (Rousseeuw 1984) approach can automatically estimate the threshold value for plane estimation (Gallo et al. 2011). Although using LMedS is slower than then using RANSAC, LMedS has an advantage in the use of point clouds with unclear outliers. Figure 2 shows an example of surface estimation results with LMedS, and indicates that stripy noises can be removed with LMedS and that parts of detailed surfaces such as draining edges remain. However, parts of stripy noises remain in point clouds. Figure 3 describes the processing result. The horizontal axis indicates the horizontal plane, and the vertical axis indicates the height. A plane can be estimated from point clouds with LMedS. Moreover, stripy noises can be recognized as outliers. However, when stripy noises are removed, parts of detailed parts are also removed because the height of stripy noises and detailed parts are generally unknown parameters. Thus, Figure 3 indicates that it is difficult to use the plane estimation approach to remove stripy noises from point clouds while ensuring that the point clouds have sufficient detail.

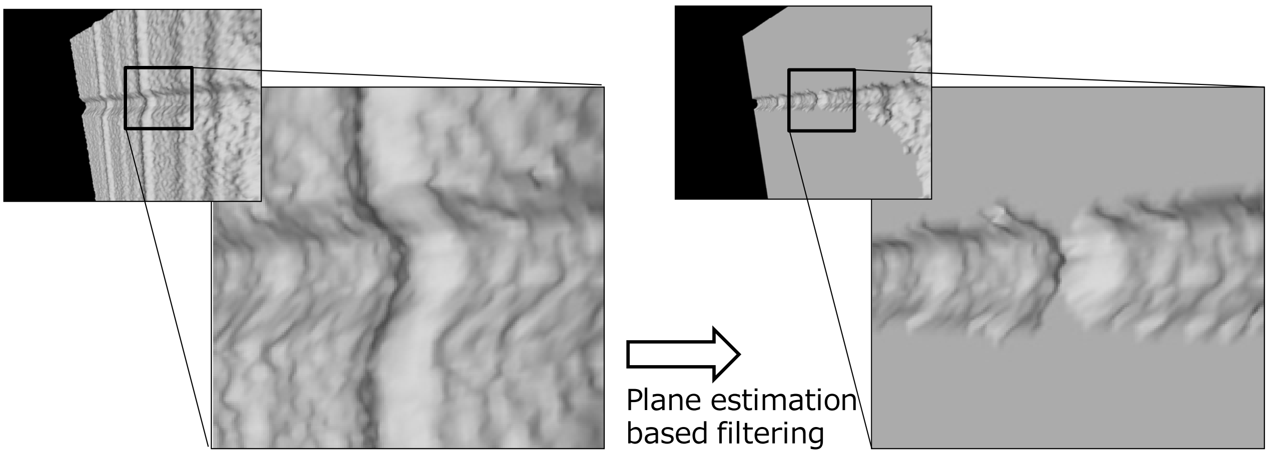

Figure 2. Surface estimation result from point clouds with LMedS

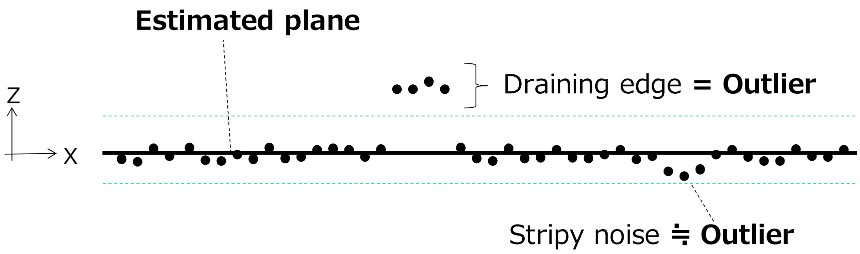

Figure 3. Outlier filtering from point clouds with the plane estimation approach

In this paper, we propose two methodologies, namely multiple data subtraction and noise pattern estimation, to remove the stripy noises for precise 3D bridge modeling. Our two methodologies were evaluated through experiments using terrestrial laser scanning data taken under a road bridge.

2. METHODOLOGY

The stripy noise appearance mechanism is shown in Figures 4 and 5. First, when a terrestrial laser scanner is installed under a bridge and across the bridge length direction (scanner installation pattern A in Figure 4), the acquired distance value of the measured point is D in laser scanning. During the laser scanning, the measured distance decreases due to slab bending with active loading. Based on this phenomenon, the new distance would be $D - d$. The time difference of the scanning rotation direction is larger than that of the scanning direction when measuring using the terrestrial laser scanner. Thus, when the active loading occurs when vehicles are on a bridge, stripy noises approximated as sine waves occur along the scanning rotation direction. In contrast, when the terrestrial laser scanner is installed along the bridge length direction (scanner installation pattern B in Figure 5), stripy noises occur across the bridge length direction.

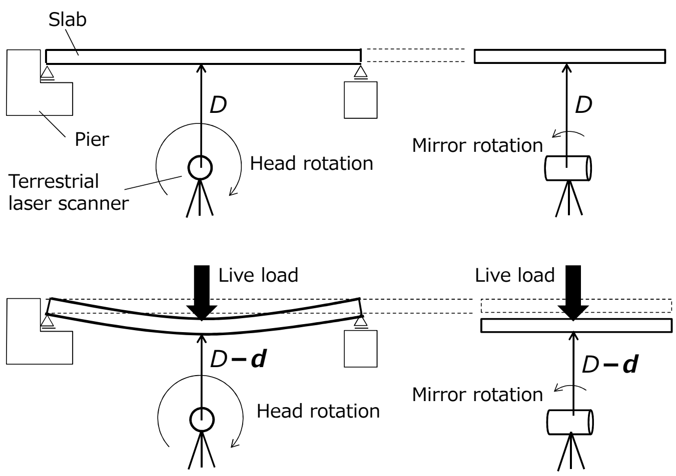

Figure 4. Stripy noise appearance mechanism. Scanner installation pattern A

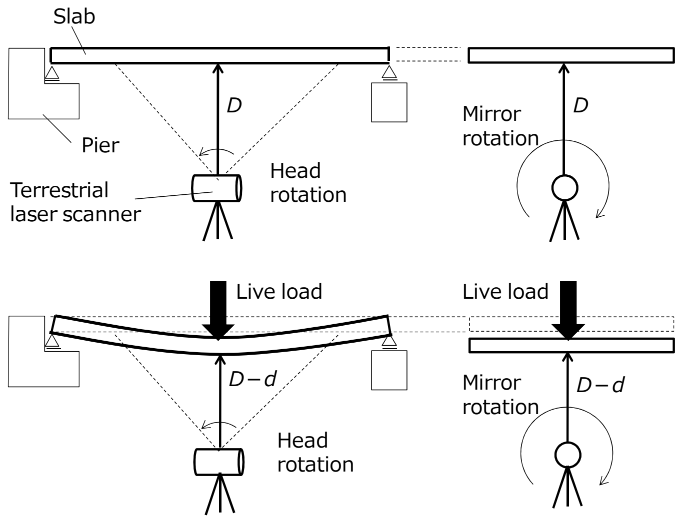

Figure 5. Stripy noise appearance mechanism. Scanner installation pattern B

We propose two approaches to remove stripy noises from point clouds. The first is multiple data subtraction using multiple acquired laser scanning data, and the second is noise pattern estimation using single scanning data.

2.1 Multiple data subtraction methodology

In multiple data subtraction methodology, multiple scanning data are used as input data. The scanning data must be acquired from the same position and rotation. When we acquire point clouds under a bridge, the stripy noises appear under the measured surface. Consequently, stripy noises are removed, as shown in Figure 6.

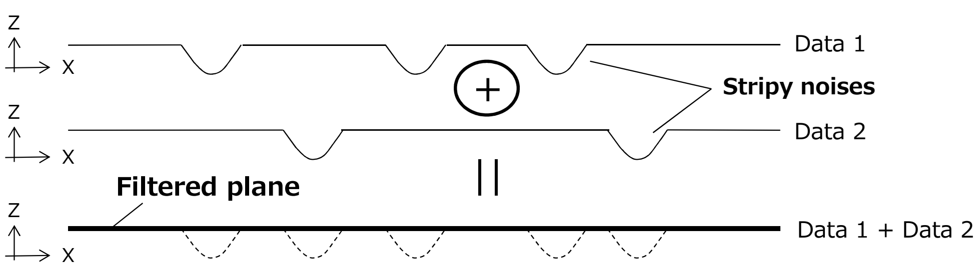

Figure 6. Multiple data subtraction methodology

2.2 Noise pattern estimation methodology

Although multiple data subtraction methodology can remove stripy noises easily, several scans are required for the data processing to remove stripy noises from point clouds. Thus, using the multiple data subtraction methodology decreases the efficiency of on-site work. Therefore, to improve the efficiency of on-site work, we propose noise pattern estimation methodology using single scanning data, which consists of four steps, as shown in Figure 7.

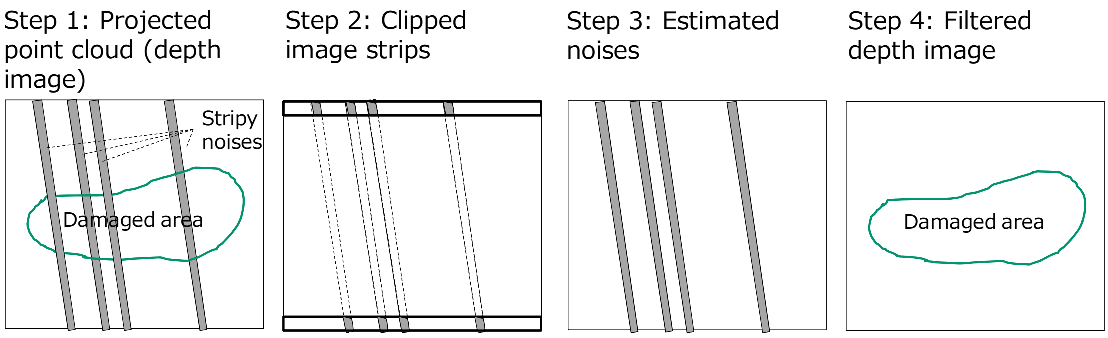

Figure 7. Noise pattern estimation methodology

In the first step, clipped point clouds are rendered to generate a depth image. Spatial interpolation processing (Nakagawa, 2013) is applied for the point cloud rendering to generate a full-filled rendered depth image. The rendered depth image retains 3D coordinate values, color values, and intensity values in each pixel. In the second step, the depth image is clipped to generate two image stripes with edges of stripy noises. In the third step, stripy noises are estimated in the depth image based on linear interpolation processing. In the fourth step, stripy noises are removed from the depth image rendered in the first step, and point clouds are reprojected to a 3D space from the depth image.

3. EXPERIMENTS

We selected a road bridge (continuous box girder; 22.8 m width and 82.2 m length) as a measured object, as shown in Figure 8.

Figure 8. The measured bridge. Left image: general view; right image: acquired point clouds

We acquired dense point clouds with a terrestrial laser scanner (VZ-400, RIEGL) on December 14, 2015 and the acquired dense point clouds are shown in Figure 9. Left images show a scanning result across the bridge length direction (scanner installation pattern A), and right images show a scanning result along the bridge length direction (scanner installation pattern B). In our experiment, the terrestrial laser scanner was installed under a bridge slab. We set the scanning angle pitches in both scanning direction and rotation as 0.003 to acquire dense point clouds of damaged areas on a bridge slab with approximately 0.5 mm spatial resolution at a distant of 10 m. Scanning times were set as approximately 0.00008 s in the scanning direction and 0.16 s in the scanning rotation direction. We selected multiple scanning data that included parts such as peeled concrete surfaces and exposed reinforcing rods in concrete. Selected scanning data were acquired from 14:00 to 15:00. During this time, we observed that several trucks crossed the bridge per a minute; the measurement details are shown in Table 1.

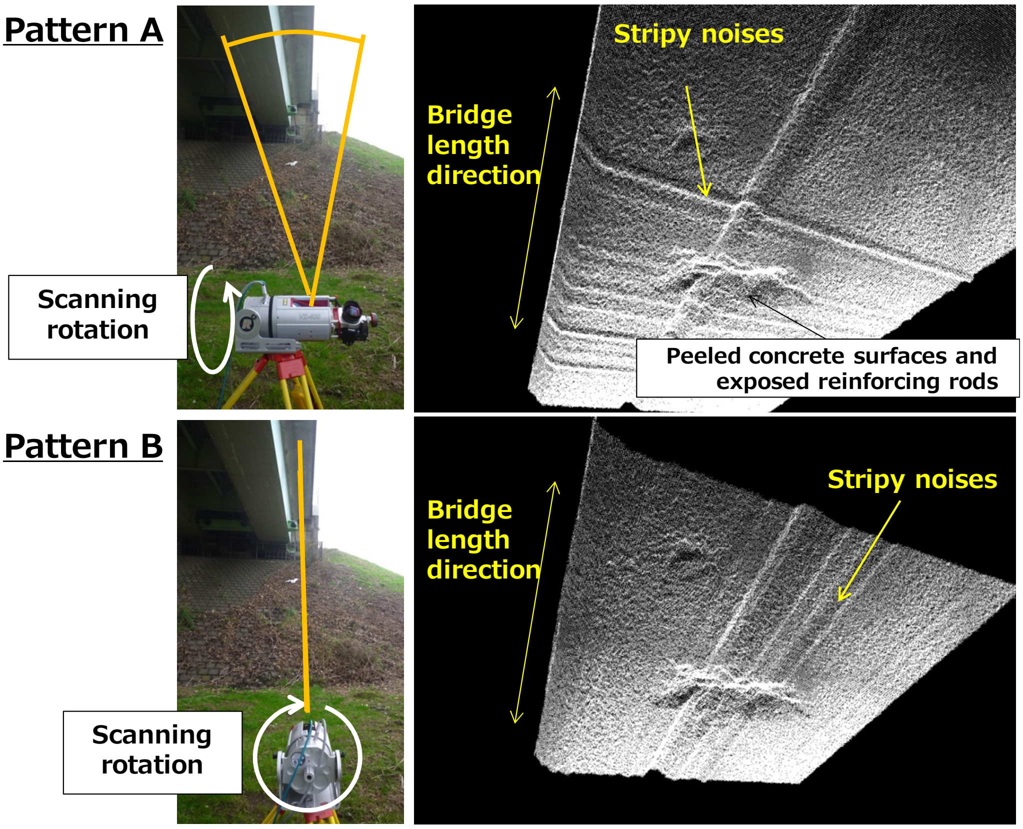

Figure 9. Acquired dense point clouds

Table 1. Measurement details

Dataset number		1	2	3	4
Scanner installation pattern		A	B	B	B
Data acquisition time		14:03	14:26	14:43	14:48
Scanning pitch angle		0.003°	0.003°	0.003°	0.003°
Scanner position	X	-0.467	-0.588	-0.588	-0.588
	Y	12.813	12.681	12.681	12.681
	Z	-0.069	-0.079	-0.079	-0.079
Scanner rotation	Roll	-19.24	116.507	116.507	116.507
	Pitch	-86.353	-88.525	-88.525	-88.525
	Yaw	-65.421	-117.747	-117.747	-117.747
The number of point		1,245,169	653,183	653,393	653,418

4. RESULTS

4.1 Multiple data subtraction methodology

In multiple data subtraction methodology, three point clouds acquired with scanner installation pattern B were used as input data (Figure 10). The left images show mesh models generated from input point clouds, and the right images show depth images generated from input point clouds. Overall, Figure 10 shows that stripy noises exist in input point clouds.

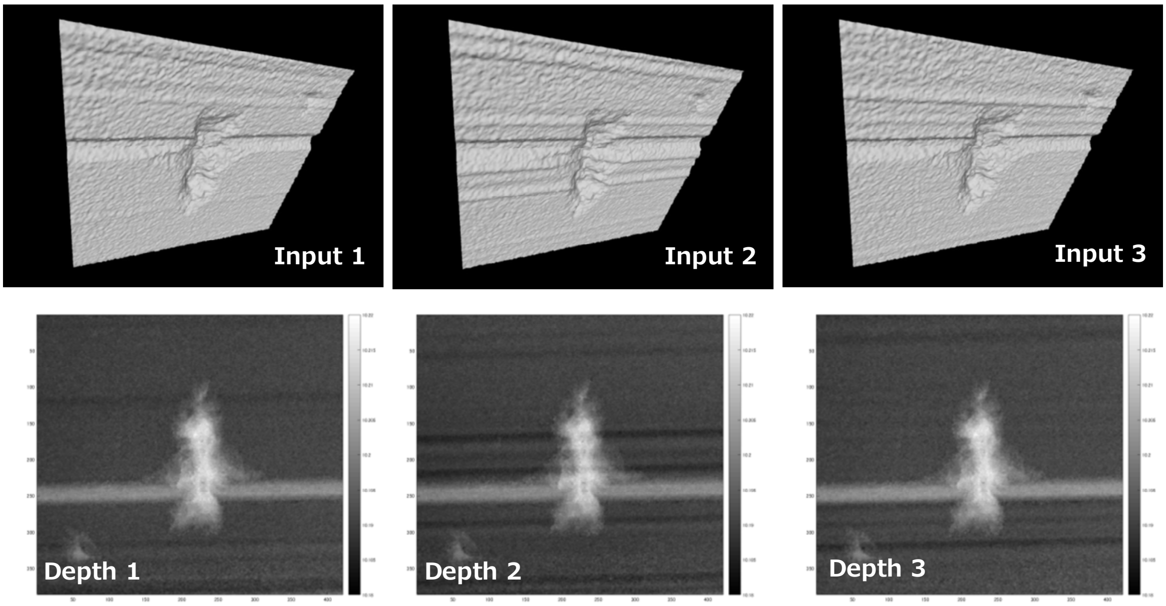

Figure 10. Three input data for multiple data subtraction processing

Figure 11 shows that the stripy noises were filtered using the three input point clouds, and that they disappeared from the input point clouds. However, although noises were filtered, Figure 11 also shows that the surface details remained in the output data. The processing environment was Matlab with a single thread (Intel i7-6567U, 3.3 GHz). In multiple data subtraction methodology, the processing time was 0.12 s, thereby confirming that this approach can achieve high processing speeds.

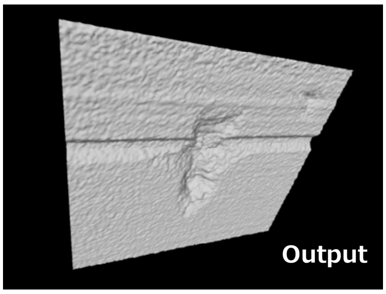

Figure 11. Noise filtering result with multiple data subtraction methodology

4.2 Noise pattern estimation methodology

In noise pattern estimation methodology, single-shot point clouds acquired with scanner installation pattern A were used as input data, and the noise filtering result is shown in Figure 12. We can see that the stripy noises disappeared in the output data. Although noises were filtered, Figure 12 also shows that the surface details remained in the output data.

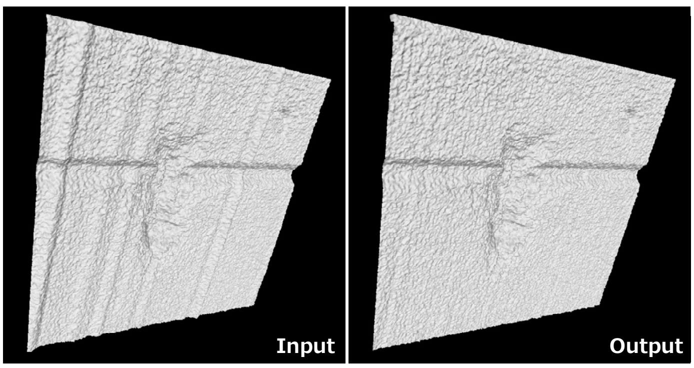

Figure 12. Noise filtering results with noise pattern estimation methodology. Mesh models

Figure 13 shows the noise filtering results, and indicates that the stripy noises were estimated from input depth data. The processing environment was also Matlab with a single thread (Intel i7-6567U, 3.3 GHz). In noise pattern estimation methodology, the processing time was 0.35 s, thereby confirming that this approach can also achieve high processing speeds.

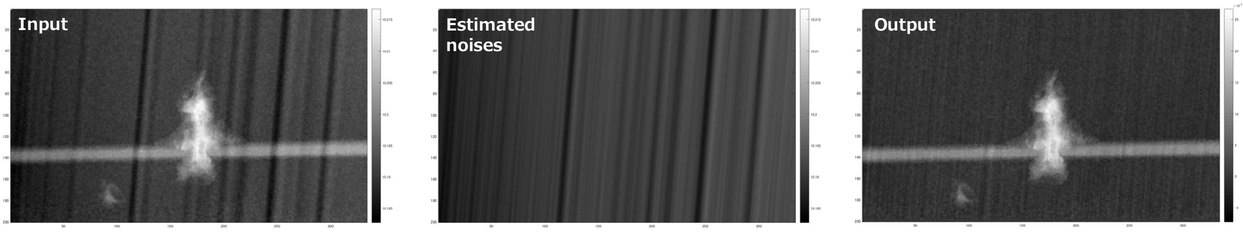

Figure 13. Noise filtering results with noise pattern estimation methodology. Depth images

5. DISCUSSION

First, we compared plane estimation methodology, as a conventional approach, with multiple data subtraction methodology and noise pattern estimation methodology (Table 2). In multiple data subtraction methodology, although multiple data should be acquired at the same position, we verified that the multiple data subtraction methodology can allow free scanning directions in scanner installation. In contrast, we confirmed that the measurement efficiency of multiple data subtraction methodology was lower than that of noise pattern estimation methodology. When measurement time limitation exists in laser scanning work, noise pattern estimation methodology is a better approach than the multiple data subtraction methodology for quick measurements. We confirmed that the noise pattern estimation methodology can remove stripy noises from the acquired point clouds even if only scanning a single dataset. However, scanner installation is restricted. When linear features such as draining edges are along the scanning direction, as shown in Figure 10, stripy noises remain. Thus, with noise pattern estimation methodology, setting the scanning direction to be orthogonal to the bridge direction is preferred.

Table 2. Comparison of the plane estimation approach, multiple data subtraction methodology, and noise pattern estimation methodology

	Plane estimation methodology	Multiple data subtraction methodology	Noise pattern estimation methodology
Scanner installation pattern	No restriction	No restriction	Pattern A is preferable
Required number of data acquisition	1 time	Several times	1 time
Data processing speed	Slower	Higher	Moderate
Noise filtering quality	Low	High	High

Second, we evaluated the accuracy of noise pattern estimation methodology, as shown in Figure 14. We verified that differences of Z (height) values of flat areas between input and output data exist within a range of laser scanning measurement accuracy (5 mm). We also verified that the positions of stripy noises had large differences of Z (height) values between input and output data, as shown in samples 1–4 in Figure 14. Thus, we confirmed that our methodology removed stripy noises from point clouds. However, sample 5 in Figure 14 shows that stripy noise remained in point clouds. Although the stripy noises were invisible in the output depth image, the stripy noise pattern estimation accuracy was not satisfactory in sample 5.

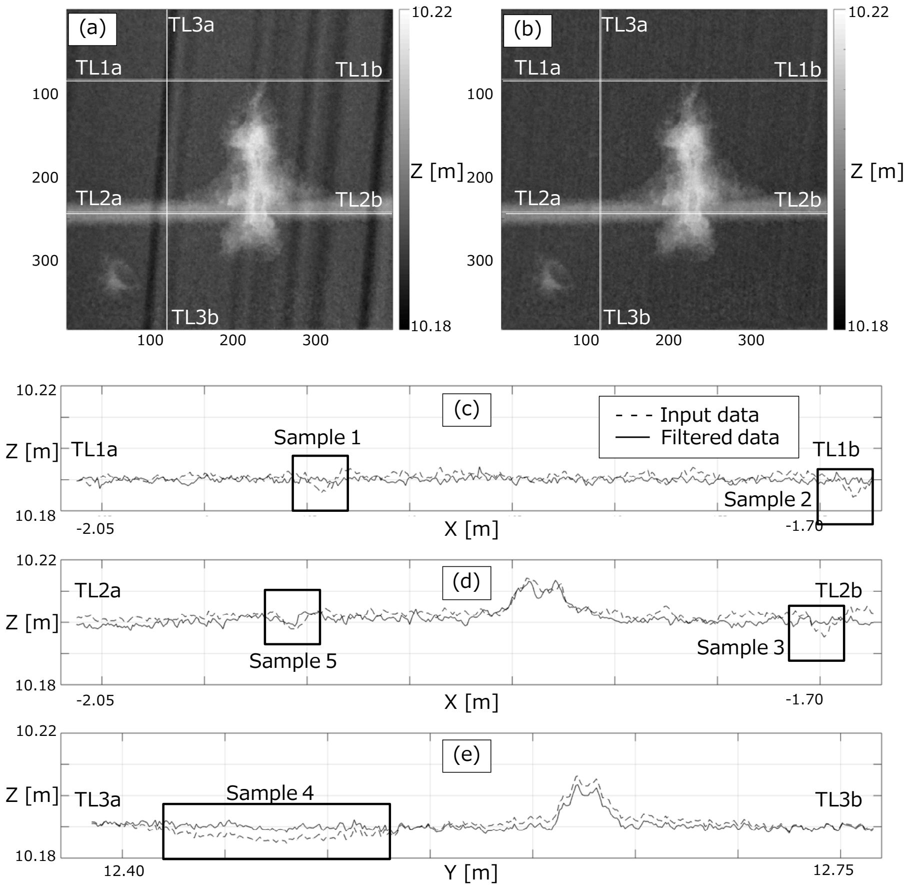

Figure 14. Accuracy evaluation of noise pattern estimation methodology: (a) three baselines in the depth image generated from input data; (b) three baselines in the depth image generated from output data; (c) section of baseline TL1a–TL1b; (d) section of baseline TL2a–TL2b; (e) section of baseline TL3a–TL3b

6. CONCLUSION

We proposed two methodologies to remove stripy noises from point clouds acquired with a terrestrial laser scanner: multiple data subtraction and noise pattern estimation. The two methodologies were verified using terrestrial laser scanning data taken under a road bridge. Experimental results confirmed that our algorithms can automatically cancel slab-bending effect of a bridge in laser scanning works.

REFERENCES

Bosché, F., Ahmed, M., Turkan, Y., T. Haas, C., Haas, R., 2015. The value of integrating Scan-to-BIM and Scan-vs-BIM techniques for construction monitoring using laser scanning and BIM: The case of cylindrical MEP components, Automation in Construction, Volume 49, Part B,.201-213.

Fischler, M.A., Bolles, R.C., 1981. Random sample consensus: a paradigm for model fitting with appli-cations to image analysis and automated cartog-raphy, Comm. ACM, Vol.24, No.6, 381–395.

Rousseeuw, P. J., 1984. Least Median of Squares Regression. Journal of the American Statistical As-sociation, 871-880.

Gallo, O., Manduchi, R., Rafii, A., 2011. CC-RANSAC: Fitting planes in the presence of multiple surfaces in range data, Pattern Recognition Letters, Volume 32, Issue 3, 1, 403-410.

Nakagawa, M., 2013. Point cloud clustering for 3D modeling assistance using a panoramic layered range image, Journal of Remote Sensing Technolo-gy, Vol.1, Iss.3, 10 pages.