TECH**NOTE**

Pocket Lidar for Trench Measurement

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This document is a technical summary of a case study for the FHWA report *Leveraging Pocket Lidar for Construction Inspection and Digital As-Builts—Phase 1* (Forthcoming).

OVERVIEW

Utility trenches provide an underground passageway for long-distance transporting utilities such as water, sewage, electricity, natural gas, and so on to minimize disruption to the built environment as well as avoid damage caused by activities above ground. Installation and maintenance of these subterranean utility lines can be challenging as these processes often involve excavation and digging, which can be time consuming and labor intensive and sometimes can result in damages to the cables and pipes. Thus, having detailed location and geometric information of the trenches to avoid these problems is highly beneficial. This information can be digitally recorded during installation, inspection, or maintenance procedures and subsequently leveraged for future maintenance and repairs. Detailed as-built information can also enable more accurate analysis to support urban planning and decisionmaking, especially for underground infrastructure.

Traditionally, such tasks were completed with basic hand tools and survey equipment. However, these approaches usually suffer from limited accessibility in and near the trenches, safety hazards from extensive time on site, and the limited number of measurements that can be captured. Therefore, comprehensively depicting trenches and utility lines in a timely manner can be challenging. With the rapid evolvement of light detection and ranging (lidar) technology, several smartphone and tablet models are now equipped with pocket lidar (PL) sensors. These small, remote-sensing devices can support generating three-dimensional (3D) models of open pits and trenches without physical contact. Compared with survey-grade, terrestrial lidar systems, these smart devices are easily accessible with minimal training needs given the availability of a variety of easy-to-use apps.

In this case study, the research team collaborated with the Pennsylvania Department of Transportation (PennDOT) to perform the following tasks:

- Assess the ability of PL to perform 3D reconstruction of a trench and the accuracy of that 3D reconstruction.
- Evaluate the accuracy of derivative metrics extracted from the PL point cloud data, such as volume or pipe dimensions.
- Analyze and discuss the opportunities and challenges of using PL to measure trenches and utility lines.

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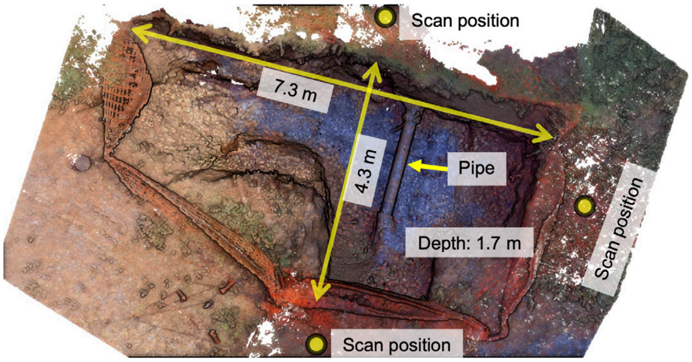
DATA COLLECTION AND FIELD SITE

The research team coordinated with PennDOT before field deployment to identify candidate sites suitable for this case study. The primary research site is a trench under maintenance located near the PennDOT Materials Testing Laboratory (figure 1).

Before the field effort, the research team gave a presentation to PennDOT about the key findings from the lab and field testing conducted in earlier phases of the research. Then the team deployed an Apple® iPhone® 13 Pro Max unit to the study site and performed data collection while PennDOT personnel also surveyed the site with a terrestrial lidar scanner (TLS): the Trimble® SX12 scanning total station.

PennDOT acquired TLS data from three scan positions around the trench (figure 2) to ensure the data quality (e.g., accuracy, coverage, and resolution). Although the range of the scanner is well beyond the area and object of interest, multiple scans are required due to the minimum vertical angle (−60°) and occlusions generated by objects and topography. Covering certain areas and objects inside a trench (e.g., the bottom surface of and area below a pipe) is still challenging given the constraints of setting up a scanner on a tripod in a safe and stable position. A lightweight scanner can be transported up and down the ladder and in the trench with ease, especially compared to heavier, tripod-based scanners (figure 3). Additionally, the field crew operating the heavier scanner can cause significant occlusions or artifacts in the data if the scanner is blocked due to limited space and mobility in the trench.

Figure 2. Illustration. Reference point cloud data collected with Trimble SX12 terrestrial lidar scanner.



Source: FWHA. Created using data from the SX12 visualized in CloudCompare version 2.13.(2)

During data collection with PL, the research team used Laan Labs® 3D Scanner App with optimized settings because it was found to be a promising app for construction inspection from previous tests and case studies.(3,4) The maximum range of the PL device is 5 m, and the data collection provided a reasonable coverage of the trench by acquiring data along the perimeter (figure 4) without entering the trench. An extension pole allows the inspector to stay further from the edge of the trench while still maintaining good coverage of the pit. Moreover, compared

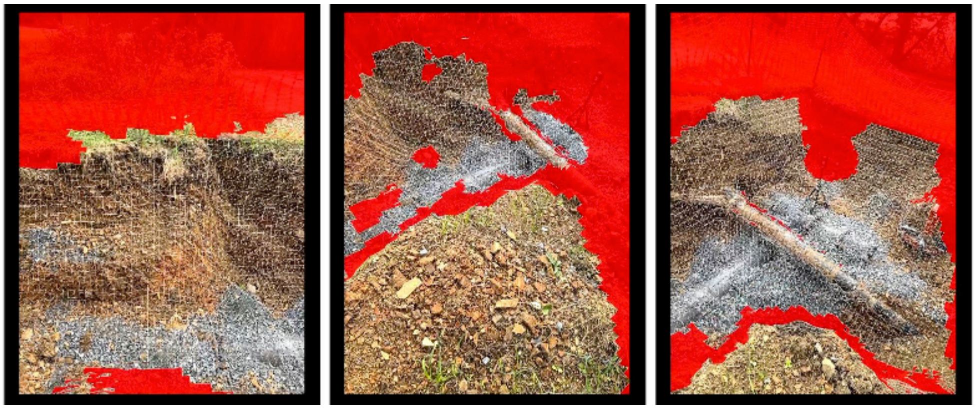
Figure 1. Photo. Case study site.

© 2024 Google® Maps™. Original photo: Airbus®, Maxar Technologies. Modified by FHWA (see Acknowledgments section).(1)

Figure 3. Photos. Example potential scan positions to cover inside a trench with a lightweight terrestrial lidar scanner.

Source: FWHA.

Figure 4. Screenshots. Data collection session with 3D Scanner App where areas beyond the sensor range are masked.(3)



Source: FWHA. Created using 3D Scanner App.(3)

to terrestrial lidar systems, PL is substantially smaller and lightweight; an inspector can easily carry PL down to the trench and perform detailed scanning if required. Figure 5 shows the resultant point cloud from PL. Some of the data gaps shown in the screenshot are caused by the orange mesh construction safety fences around the trench.

DATA PROCESSING

The terrestrial lidar data were registered by PennDOT and shared with the team. The original data were high resolution (subcentimeter level) with U.S. survey foot units of measurement. To keep the unit consistent with the PL data and reduce the data volume to speed up subsequent processing and analysis, the data were converted to meters and downsampled to a 0.01-m point density with the EZDataMD EZVox tool.(5)

Figure 5. Screenshot. Point cloud data of the trench obtained with PL.

Source: FWHA. Created using data from 3D Scanner App visualized in CloudCompare version 2.13.(2,3)

To register the point clouds in the same coordinate system, the terrestrial lidar and PL data were registered in CloudCompare version 2.13.(2) First, one point cloud dataset was manually translated and rotated to match the other. Then an automatic fine alignment process was performed using the iterative closest point algorithm to minimize error between the two datasets.(6) Both alignment procedures did not adjust the tilting of either scan for evaluating the accuracy of the leveling quality with PL. The root mean square (RMS) error—a common metric used to quantify the registration accuracy—of the final registration was 0.048 m.

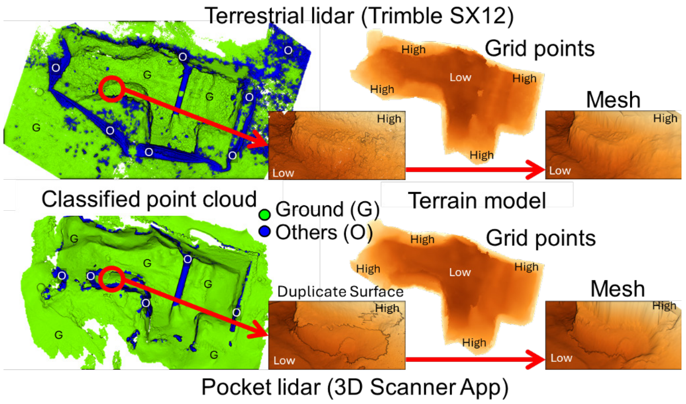
To further separate the ground surface from other objects, EZDataMD's Vo-SmoG ground-filtering tool was used for both datasets with the same parameter settings (table 1).(7) The parameters were established by considering various factors, such as data resolution and quality. A paper by Che, Senogles, and Olsen contains a detailed description of the Vo-SmoG algorithm and that algorithm's parameters.(8) Because the mesh fences and low vegetation surrounding the trench can potentially increase the possibility of false negative classification results, the point clouds were first filtered based on the same elevation thresholds. This same elevation threshold in the local coordinate system was also used as the ground level in further analyses, such as volume estimation. A 2 1/2-dimensional (2.5D) point grid was generated from the ground points to help with terrain modeling and comparison of the data. The grid cell size was set to 0.03 m and the maximum data gaps to be interpolated were set to 3 m. Lastly, the point clouds and terrain models were cropped to the same spatial extents for consistency in comparisons and calculations in the analyses.

Figure 6 shows the ground-filtering and modeling results for the terrestrial lidar and PL data. When evaluating the Vo-SmoG ground-filtering results, the terrestrial lidar data captures the mesh fence and vegetation in detail, while PL generates a smoother surface in general because PL had difficulty capturing the objects.(7) The pipe in the trench is correctly classified in both data as nonground. When further comparing the results, some artifacts occur in the PL data. Two surfaces appear to be overlapping in a specific area (highlighted in figure 6). This inconsistency in the surface is likely caused by the misclosure errors from the PL device and app, because this area happens to be near the starting and end points of the data-collection session. In this case, as shown in the results, the ground-filtering and modeling processes tend to treat the lower surface as the ground surface and remove the upper surface.

Table 1. Key parameter settings in the Vo-SmoG ground-filtering tool.(7)

Parameters	Values
Isolated point removal window	0.30 m
Low point filtering window	0.05 m
Normal estimation window	0.10 m
Seed selection window	3.00 m
Proximity filtering window	0.03 m
Maximum normal difference	5°
Maximum displacement	0.03 m
Maximum gap	3.00 m
Minimum size	100 cells
Proximity distance	0.03 m
Maximum iterations	3

Figure 6. Illustrations. Ground-filtering and terrain-modeling results of the point cloud data from the terrestrial lidar and PL data.



Source: FWHA. Created using data from the SX12 and 3D Scanner App visualized in CloudCompare version 2.13.(2,3)

ANALYSES

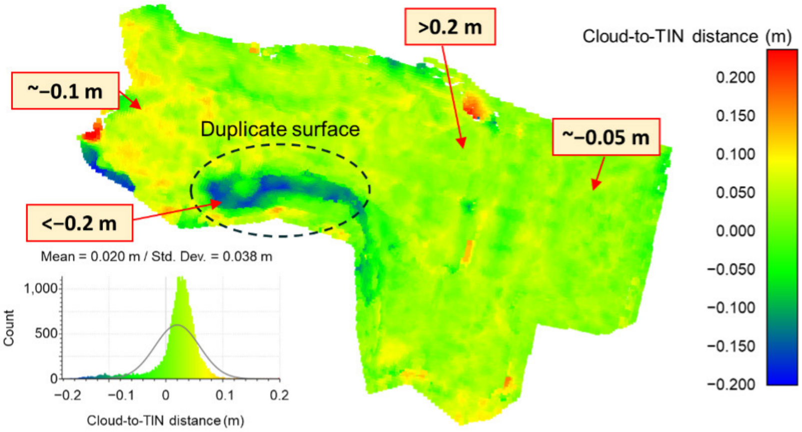
Cloud-to-TIN Comparison

To evaluate the effectiveness and accuracy of using PL to model a trench, the team used CloudCompare to create the reference triangulated irregular network (TIN) model—using the terrestrial lidar data—by performing a Delaunay triangulation of the grid points.(2) Next, the distance between each grid point from processed PL data to the reference mesh was computed, followed by statistical analysis (figure 7). The mean and standard deviation of the cloud-to-TIN distances were 0.020 m and 0.038 m, respectively. This bias and variation between the surfaces were similar to the RMS reported in the registration process. Additionally, the distribution of the cloud-to-TIN distance follows a Gaussian distribution, which indicates that most of the errors were likely random errors in range measurements. Nevertheless, the same area with artifacts observed due to misclosure showed significantly larger errors compared with other areas (duplicate surface identified in figure 7). Another reason for such errors is the steep slope in this area; steep slopes tend to result in more artifacts in 2.5D-grid and TIN models.

Volume Estimation

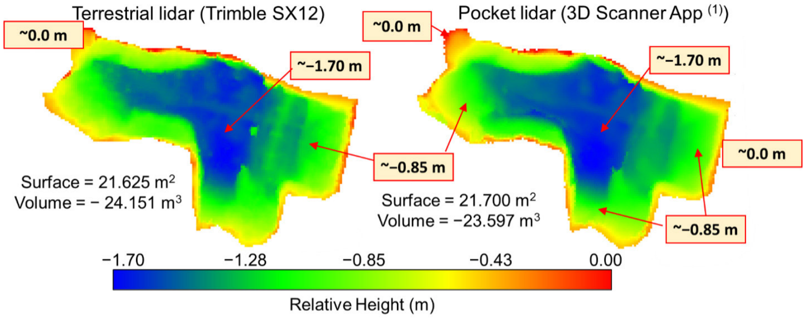
The team used CloudCompare to estimate the volume excavated from the trench for both terrestrial and PL datasets.(2) For each point cloud (ground points gridded at 0.03 point spacing), the same parameters were applied to ensure the estimation's consistency. A horizontal plane was defined at ground level (0.35 m in the local coordinate system, which is the same plane used for elevation filtering). This ground-level plane was then used as the reference surface for volume calculations. The cell size was set to 0.05 m, resulting in a raster with dimensions of 156-by-109 (17,004 cells, including empty cells outside the area of interest). The cell size was set slightly larger than the input point density to minimize the empty cells in the area of interest. In each cell, an average elevation was taken among all the points lying inside the cell. Figure 8 shows the rasterization and calculation results. The two-dimensional (2D) surface area for each dataset was also calculated for quality control, because the 2D surface area should be very close between the two point clouds (21.625 m^2 and 21.700 m^2, respectively). The volume estimates from terrestrial lidar and the PL point cloud are 24.151 m^3 and 23.597 m^3, respectively. The volume measurement from the PL data is only 0.554 m^3, or 2.3 percent, less than the reference volume derived from terrestrial lidar data.

Figure 7. Illustration. Cloud-to-TIN comparison between PL and terrestrial lidar data.



Source: FWHA. Created using data from the SX12 and 3D Scanner App visualized in CloudCompare version 2.13.(2,3)
Std. Dev. = standard deviation.

Figure 8. Illustrations. Volume calculation results for PL and terrestrial lidar data.



Source: FWHA. Created using the SX12 and 3D Scanner App visualized in CloudCompare version 2.13.(2,3)

Pipe Modeling

The characteristics of the pipes exposed in the trench are valuable information for utility inspection and maintenance. After the ground-filtering process, the pipes were included in the nonground points for both terrestrial and PL data, which simplifies the extraction of such features. After manually segmenting the pipe from the point cloud in each dataset, modeling was performed with the Random Sample and Consensus (RANSAC) algorithm in CloudCompare with the settings defined in table 2.(2,9) RANSAC is a common approach for geometric primitive fitting that randomly samples points from the point cloud to generate shapes and identifies the consensus between these point sets from multiple iterations of random sampling to identify the predominant shape.

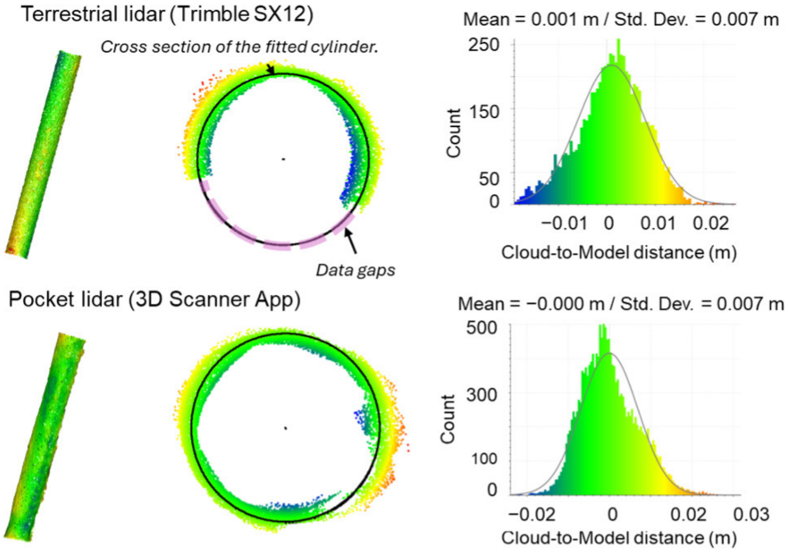
The modeling process succeeded in fitting a cylinder to both datasets. To evaluate the quality of the fit, the distance between each point cloud to the corresponding primitive (i.e., the best-fitting cylinders) was calculated and analyzed (figure 9). No significant differences were observed between the two datasets in terms of the mean (0.001 m and 0.000 m for terrestrial lidar and PL, respectively) and standard deviation of the errors (0.007 m for both datasets). However, the terrestrial lidar data can be visually observed to contain less noise but have data gaps due to the limited line-of-sight from the scan positions, as discussed in the Volume Estimation section. As a result, the least squares best-fitting primitive could potentially be biased and more sensitive to noise. By contrast, although more errors are present in the PL data, the PL data have more complete coverage of the pipe, which can help balance the modeling calculations in the fitting process.

Table 2. Key parameter settings in RANSAC cylinder fitting.(9)

Parameter Settings	Value
Minimum support points per primitive	Yes
Use least squares fitting on found shapes	Yes
Primitives	Cylinder only
Maximum distance to primitive	0.030 m
Sampling resolution	0.010 m
Maximum normal deviation	35°
Overlooking probability	3 percent

To further evaluate the accuracy of the model derived from PL data, a detailed comparison between the computed parameters of the cylindrical models was conducted (table 3). Overall, the results are promising for measuring the basic characteristics of the pipe in the trench with PL, with generally consistent results to the terrestrial lidar data. Many characteristics can also be impacted by the modeling approaches and algorithms. For example, the length of the cylinder heavily depends on the segmentation and extraction of the point cloud lying on the pipe, which can be a subjective process. Additionally, the horizontal

Figure 9. Illustrations. Modeling results of the pipe in the PL and terrestrial lidar data.



Source: FWHA. Created using data from the SX12 and 3D Scanner App visualized in CloudCompare version 2.13.(2,3) orientation of the pipe can be affected by the registration accuracy and strategy in this case. Similarly, the difference in radius can be partially explained by the ranging errors of the PL itself, as well as the potential bias introduced to the terrestrial lidar data due to lack of coverage for the bottom of the pipe. The tilting angle (slope) is an important attribute for a water or sewage pipe to ensure the flow direction. In this case, PL shows high accuracy in measuring the tilting angle via the cylindrical model.

Table 3. Comparison between best-fitting cylinders from terrestrial lidar and PL.

Statistics	Terrestrial Lidar (SX12)	PL (3D Scanner App)[3]	Difference
Point count	6905 (sampled to 0.01 m)	16697	—
Mean error (m)	−0.000	0.001	0.001
Std. dev. error (m)	0.007	0.007	0.000
Radius (m)	0.089	0.097	0.008 (9.0%)
Length (m)	1.712	1.728	0.016 (0.9%)
Axis	(0.2440, 0.9667, 0.0772)	(0.2636, 0.9616, 0.0765)	1.16°
Tilt (degree)	4.43	4.39	−0.04 (−0.9%)

—No data.

KEY FINDINGS AND FUTURE OPPORTUNITIES

Some of the key findings and future opportunities from this case study are summarized as follows:

- PL apps are easy to use and can provide coverage in realtime, such that the inspector is able to ensure the data quality, which is particularly helpful in capturing trenches at busy construction sites to ensure the data quality is sufficient before leaving the site.
- PL's size and weight provide great flexibility in terms of how and where to capture the data, especially in the limited working area associated with trenches.
- An extension pole is highly recommended if an inspector deploys a PL device to collect data within a trench because an extension pole can significantly increase coverage while allowing the inspector to work from a safe location. An extension pole also helps minimize the amount of field-of-view blockage by PL while the inspector is navigating rough terrain.
- Mild misclosure errors can be found when capturing a trench shorter than 10 m in any dimension in a loop. However, for a trench longer than 10 m, consider using multiple data-collection sessions with overlapping areas between them to minimize drifting and misclosure issues.
- PL shows accurate results calculating the volume of the trench. An approximate volume estimate can be obtained in some apps with a little bit of processing in the field.
- Pipes can be extracted and modeled in the PL data during postprocessing. However, the diameter of the pipe must be 0.05 m or larger for the pipe to be adequately captured.
- The modeling accuracy for the pipes from the PL data is promising in terms of the dimensions (i.e., length and radius) and tilting angles. The horizontal orientation of the pipes can also be estimated as some apps leverage the navigation data in the device.
- AR and mixed-reality technologies enable visualization of the data at the actual location, even after the trench or pit is filled because Global Navigation Satellite System georeferencing information can be captured during the scan. Future maintenance and construction can greatly benefit from such 3D visualization, which helps minimize guesswork in excavation.

ACKNOWLEDGMENTS

The original map in figure 1 is the copyright property of Google® Maps™ and can be accessed at https://www.google.com/maps/@40.2889958,-76.8657642,215m/data=!3m1!1e3?entry=ttu.(1) The map was modified by the authors to show the location of the trench.

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Researchers—This study was conducted by EZDataMD, LLC; 5C Strategy; and MPN Components, Inc. in collaboration with PennDOT. Ezra Che (EZDataMD, LLC), Michael Olsen (EZDataMD), John Caya (5C Strategy), and Gene Roe (MPN Components, Inc.) were researchers under order number 693JJ321P000047. Michael Barrett, Sherry Hartman, Kelly Barber, and Allen Melley from PennDOT contributed to this case study.

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