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Mapping of Pavement Conditions Using Smartphone/Tablet LiDAR
Case Study: Sensor Performance Comparison

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CSUTC California State University Transportation Consortium

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16. Abstract
Poor road conditions affect millions of drivers, and assessing the condition of paved surfaces is a critical step towards repairing them. This project explores the feasibility of using the Apple iPad Pro LiDAR sensor as a cost-effective tool for assessing the damage and condition of paved surfaces. Our research aims to provide accurate and precise measurements using readily available consumer devices and compare the results to state-of-the-art equipment. This investigation involved visual inspection, identification, and classification of pavement distresses, followed by a comparison of the iPad and iPhone LiDAR data with a survey-grade terrestrial laser scanner. The project revealed several limitations of the iPad Pro-based LiDAR approach. The level of detail captured in the scans was relatively low, with a best-case resolution of 1 cm and an inability to detect smaller cracks and shallow potholes. Longer scans (in terms of both time and distance) led to geometric anomalies in the surface models. Colorized scans provided some visual contrast, aiding in the identification of damage, particularly on moderately damaged concrete surfaces. The potential sources of error were identified, including the performance of the Inertial Measurement Unit (IMU), the limitations of the LiDAR sensor itself, and the opaque nature of onboard data processing within the 3D Scanner App. Suggestions for improvement included the use of gimbal stabilizers to enhance scan quality and the exploration of more intensive PC-based processing for raw data analysis. Hardware advancements by Apple and software enhancements by app developers were also highlighted as potential areas for future improvement. While the project revealed limitations and challenges, the authors acknowledge the possibility of future hardware upgrades, augmented reality advancements, and improvements in sensor accuracy and processing. However, based on this project's findings, the iPad Pro LiDAR approach currently falls short of providing the necessary resolution and accuracy required for comprehensive roadway damage assessment. Results indicate that additional developments are necessary to address the identified limitations and make this method a viable and cost-effective solution for roadway surface evaluation.

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Executive Summary

Poor road conditions affect millions of drivers each day. As the mileage of paved roads increases, the task of monitoring the condition of each road becomes increasingly difficult. Carrying conditions are the result of weather, material, traffic, and the life cycle of the road. Methods of monitoring the conditions of roads vary from visual inspection, pictures, use of state-of-the-art LiDAR on a vehicle, or even the use of spectral data analysis. Public and private agencies should be responsible for minimizing costs to optimize budgets. Proper and timely assessments are necessary to budget and plan for future needs and to protect the welfare and safety of the public. LiDAR (Light Detection and ranging) is a technology that is utilized in many contexts for remote sensing and traditional geomatics applications. LiDAR is not a new tool for assessing the condition of road pavement. However, the cost for traditional mobile applications of LiDAR is high and is used for larger areas. Accurate positional networks require an immense amount of time to establish targets for quality control and checks, so they are not always suitable for smaller areas or those that require immediate attention. Low-cost, off-the-shelf technology has the potential to aid in the detection of smaller areas of pavement, which can facilitate proper assessment and planning to prevent and correct further issues. Apple has integrated a LiDAR sensor in the iPad Pro and the Apple iPhone Pro Model 12 and up to aid in the portrait mode at night. This project explores the application of the Apple iPad Pro and Apple iPhone equipped with LiDAR technology, using free apps that will utilize the LiDAR sensor in a more traditional Geomatics Engineering method. It will rely heavily on the IMU (inertial measurement unit), the integrated camera, and the single frequency GNSS (global navigation satellite system) sensor to position the device and to control the resultant collected data sets. A terrestrial LiDAR scanner, Leica P20, will be used as base model from which the comparison of the iPad and the iPhone will be made.

Based on testing and analysis, the Apple iPad Pro and iPhone Pro LiDAR systems are currently inadequate for detailed assessment of roadway surface damage. Sub-centimeter vertical deformations are needed to accurately define 3-D quantities which cannot be obtained with vertical accuracies in the 3-4 cm range. Multiple scans from different directions and angles would increase the ability to define the vertical deformations. However, the resulting misalignment between the same scan and multiple scans renders the created surface models useless. A general assessment is possible within the limitations of the LiDAR devices. General affected areas (square footage), relative distances, and visual damage can be measured. The cameras that are used help to identify locations of the damage, not just its extent.

1. Introduction

Pavement performance investigation and evaluation are critical for pavement management systems (PMS) to maintain suitable driving conditions and to ensure adequate funding for rehabilitation efforts (Chun, P.J., Yamane, T., & Tsuzuki, Y., 2021)(Chun, P.J., Yamane, T., & Tsuzuki, Y., 2021). For this purpose, agencies are interested in the type, extent, and severity of different types of distress. The most significant types include rutting, cracking (fatigue cracking and thermal cracking) for flexible pavement, and cracking and faulting for rigid pavement. There is specialized equipment available to identify pavement distress and quantify pavement conditions. However, the specialized equipment generally has high variability, is subject to detection errors, and requires considerable labor and cost (Chun, P.J., Yamane, T., & Tsuzuki, Y., 2021) and (Huang, J., Liu, W., & Sun, X., 2014)(Huang, J., Liu, W., & Sun, X., 2014). Therefore, a superior method to collect pavement condition data and evaluate pavement performance is needed.

Figure 1. Fatigue Cracking, Patterns, and Detection System
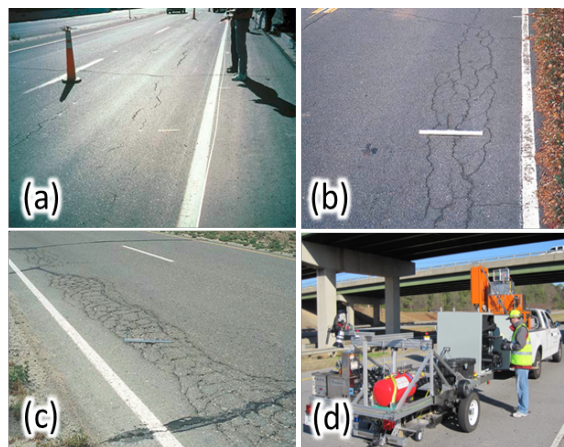
Recent technological advancement is rapidly replacing the labor-intensive and subjective visual-based inspection with a sensor-based approach. Commonly used sensors include digital cameras, Unmanned Aerial Vehicles (UAVs), line cameras, 3D Laser Imaging, and terrestrial laser scanners (Ragnoli, A., De Blasiis, M.R., & Di Benedetto, A., 2018)(Ragnoli, A., De Blasiis, M.R., & Di Benedetto, A., 2018).Cameras (mono and stereo), line cameras, and cameras on UAVs demonstrate a high success rate in identifying and measuring cracks on roads, as does 3D laser scanning, which acquires 3D images of various depths and types (Zakeri, H., Nejad, F.M., & Fahimifar, A., 2017)(Zakeri, H., Nejad, F.M., & Fahimifar, A., 2017).

Figure 2. Fresno State, Engineering East Corridor - iPad Scan

Recently, mobile phones and electronic devices began adapting new camera and 3D sensing technologies. In 2020, the Apple iPad Pro and the Apple iPhone 12 Pro were equipped with a LiDAR sensor to improve portrait-mode photos, specifically at nighttime. This new LiDAR sensor, however, has various unintended capabilities that can be adapted for other applications, including measuring pavement performance.

Figure 3. Terrestrial LiDAR Scan and Photo of Failed Pavement

Low-cost sensors enable faster identification and detection of pavement conditions and performance. Road pavement identification costs are high due to the specialized sensors required, regardless of the size of the project. This leaves small construction sites with larger fixed costs disproportional to the size of the project. iPad and iPhone LiDAR technologies can be utilized and geared towards small sites such as parking lots, construction areas, and surrounding short segments of road.

This proposal is designed to address three SB-1 objectives which incorporate: (1) new technologies; (2) cost-effective maintenance and decision-making regarding roads; and (3) long term maintenance and pavement rehabilitation requirements.

1.1 Visual Inspection

Due to road construction and aging, the Fresno State campus has many areas that display obvious signs of cracking and fatigue, known as areas of concern. The areas chosen all have horizontal identifiers to allow for visual fatigue and damage. Different pavement types have been chosen as shown in figures 5, 6, 7, 8 and 9. According to the Caltrans Concrete Pavement Guide (State of California Department of Transportation, 2015) (State of California Department of Transportation, 2015), distress can be categorized into the following classifications:

- Cracking

- Joint/crack deterioration

- Roughness

- Surface defects/durability

- Miscellaneous defects

In 2018, the Caltrans State of the Pavement Report (Caltrans Division of Maintenance Pavement, 2019) (Caltrans Division of Maintenance Pavement, 2019) details the condition of the roads across the state, classifying them from good, to fair, to poor.

Figure4. Statewide Pavement Condition Summary by Pavement Type Based on Federal Performance Measures

Federal Measure	2016 (Lane-Miles Collected)		2018 (Lane-Miles Collected)	
	Asphalt	Concrete	Asphalt	Concrete
Good	18,694	5,732	21,399	6,657
Fair	18,072	7,109	15,518	6,126
Poor	330	409	205	356
Statewide Total	37,096	13,250	37,122	13,138

Figure 4 underscores the vast mileage of roadway that Caltrans maintains, making simple and prompt classification of road conditions necessary. While this research did not use state highways, similar areas found on the Fresno State campus will demonstrate the abilities of the iPad and iPhone LiDAR sensor.

Figures 5, 6, 7, 8, and 9 below display the areas to be scanned and compared. Figure 5 shows an area near the dorms on Fresno State campus, which sees a high volume of vehicle traffic from students. It also receives a high volume of vendors delivering food to the university dining hall.

Figure 5. Site #1 on Fresno State Campus

Figure 5 details the conditions in this area, including cracking in the asphalt, patching pothole areas from construction work, and other miscellaneous defects.

Figure 6. Site #2, on Fresno State Campus, No Known Defects in the Asphalt

Figure 7. Site #1 on Fresno State Campus, Cracking, Joint Deterioration,
Roughness, Surface Defects

Figure 7, site #2, displays a newer road that was recently paved and striped, showing no known defects.

Figure 8. Site #3 Concrete Pavement - Cracking, Joint Deterioration,
Roughness, Surface Defects

Figure 8 represents site #3 of a concrete sidewalk used as a common path for students to walk or cycle between buildings on campus.

1.2 Accuracies of iPhone/iPad Pro LiDAR and Terrestrial Laser Scanner

The Leica P20 is an innovative combination of advanced, time-of-flight range measurements plus modern Waveform Digitizing (WFD) technology. It aims to achieve high-accuracy angular measurements and survey-grade tilt compensation (FLT Geosystems 2013). It can achieve detailed nuances of any scene that it scans, with a 3D positional accuracy of 3 mm at 50 m, and a linear error of less than 1 mm. The P20 is the ideal instrument to achieve an accurate surface model against which all other data will be compared.

Specifications on the iPad Pro and the iPhone are not readily available, as the original intent of the sensor was for portrait photos, not for mapping. The iPad Pro sensor's maximum accuracy is about 1cm at best accuracy (Luetzenburg, G., Kroon, A., & Bjork, A.A., 2021) (Luetzenburg, G., Kroon, A., & Bjork, A.A., 2021).

Figure 9. Leica Scanstation P20 Specifications

System Performance	
Accuracy of single measurement	
3D Position Accuracy	3 mm at 50 m; 6 mm at 100 m
Linearity error	≤ 1 mm
Angular accuracy	8″ horizontal; 8″ vertical
Target acquisition*	2 mm standard deviation up to 50 m
Dual-axis compensator	Selectable on/off, resolution 1″, dynamic range +/– 5', accuracy 1.5″

1.3 Classification of Fatigues: Surveyed vs Visual Check

Traditional inspection is done visually as shown in figure 11 (Caltrans Division of Maintenance Pavement, 2019)(Caltrans Division of Maintenance Pavement, 2019).

Figure 10. APCS Vehicle on the Road and Manual Pavement Inspection

Similarly, a proper analysis of the digital 3D inspection derived from the LiDAR data and point clouds from the iPad and iPhone will allow classification of the same areas and extent of the fatigue. An initial visual check will be performed to ensure proper coverage of the areas in question. Next, a 3D analysis will quantify the extent of the fatigue in the various pavement types.

2. Methods

2.1 Equipment Used

Scan data from an off-the-shelf iPhone and iPad Pro was compared to the Leica P20 LiDAR Scanner. After detailing its specifications, it is evident that the Leica P20 will vastly outperform the iPhone and iPad LiDAR sensor. Thus, the Leica P20 will be used as a reference for the iPad and iPhone. Our goal is to determine if we can quickly produce a deliverable that shows roadway damage accurately enough to be useful.

The Leica P20 measures 3 mm of inaccuracy on measurements at 50 m. The linearity error is equal to or less than 1 mm. The P20 can also scan up to 1 million points per second (FLT Geosystems, n.d.) (FLT Geosystems, n.d.) (Fig. 9). Conversely, the iPad Pro sensor has a maximum accuracy of approximately 1 cm (Luetzenburg, G., Kroon, A., & Bjork, A.A., 2021). As Apple has not released this information, we could not find a figure for the scan rate from a reputable source, though we can assume it is far lower than professional-grade scanners.

2.2 Types of Surfaces

Using Caltrans road classifications, we identified areas demonstrating fatigue in asphalt and concrete on the Fresno State campus. As demonstrated previously in Figures 5 through 9, areas of extreme fatigue in asphalt and concrete were used, as well as a recently paved road made of asphalt. Each surface type allows for classification from a visual inspection. The surfaces included smooth asphalt, moderately damaged asphalt, extremely damaged asphalt, and moderately damaged concrete. This included surfaces that had buckling, separation, pitting, and wash boarding.

According to the Caltrans Concrete Pavement Guide (State of California Department of Transportation, 2015)(State of California Department of Transportation, 2015), distress can be categorized into the following categories:

- Cracking

- Joint/crack deterioration

- Roughness

- Surface defects/durability

- Miscellaneous defects

2.3 Data Collection

Several iPad and iPhone scanner apps are available for use. Each app employs its own proprietary software to view 3-D data as a surface model, a 3D point cloud, or a mesh, all of which are visual depictions of the scanned objects. Several different scanning techniques were conducted during the data collection phase to determine which method produced the best results.

To collect sufficient data, linear measurements were made along crack lines and perpendicular to fatigue. The LiDAR sensor was also panned side to side and in circles around the roadway.

Long, continuous scans were compared against short and small burst-of-data measurements. The long, continuous scans included sufficient overlap of areas to ensure proper coverage.

Using a traditional terrestrial scanner, a base surface was created for comparing other scans.

2.4 Processing Data

Data from the iPhone and iPads were stored in raw formats. Each scan was converted and exported as a .las file to allow for compatibility with Leica Cyclone software.

The iPhone and iPad were processed in Leica Cyclone, a software product that can convey large point clouds and perform complex and accurate analysis. Similarly, a surface was created using the Leica P20 scanner to produce the base model/surface for comparisons. It was processed in Leica Cyclone.

3. Results

The results show that iPads and iPhones cannot be utilized at this time to make proper analyses of measurable pavement conditions.

3.1 Site #1

Site #1 served as the foundation for the level of detail attained using the iPad and iPhone LiDAR sensor. Figure 11 represents Site #1 using the base surface from the Leica P20 Scanner. Several conclusions can be made from this figure. Joint/crack deterioration is visible along the patch lines of the asphalt. Roughness is apparent. Holes in the asphalt are visible and were measured at 3-4 cm in depth. Details of infrastructure are also visible using the Leica P20 scanner. Figure 11 shows details of the manhole and joints in the curb/gutter. The rim of the manhole sits approximately 0.5 cm below the grade of the asphalt.

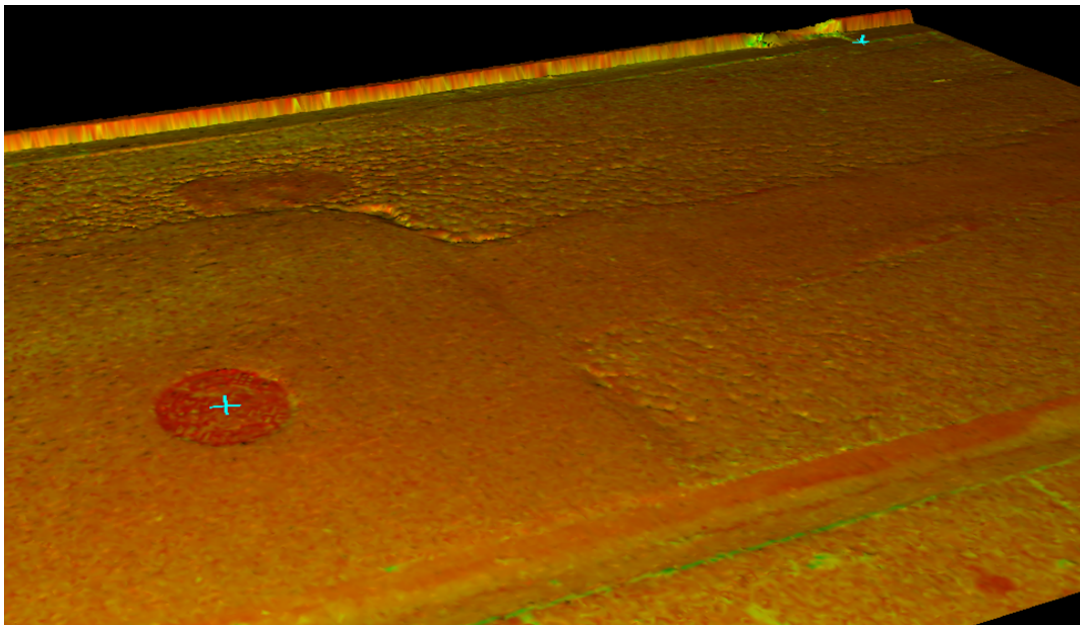Figure 11. Site #1 Leica P20 Scanner Surface

Figure 12 shows the poor results derived from the iPad LiDAR sensor. An inspection with the surface will not bear the same results. The manhole is not visible. Figure 12 shows that the road is smooth. Joints in the curb and gutter are not visible. The iPad sensor did show the hole in the asphalt, but it is nowhere near the level of detail needed to make quantifiable measurements.

Figure 12. Site #1 iPad LiDAR Sensor
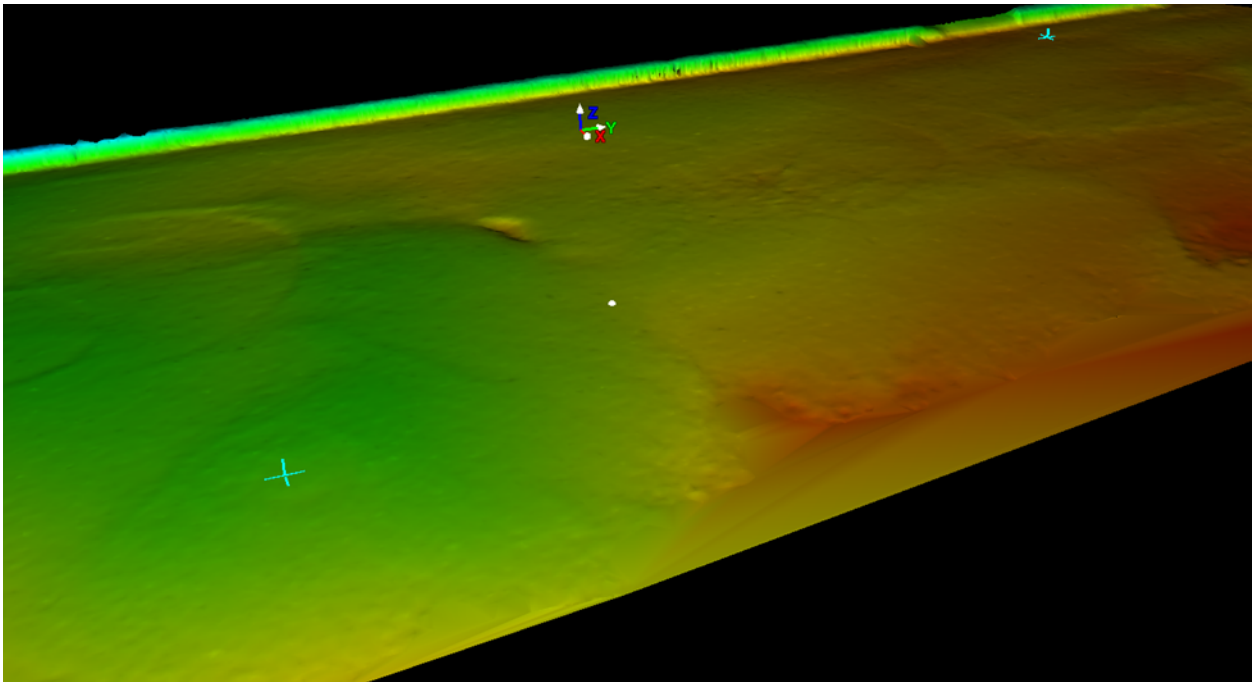
The level of detail observed on the iPad Pro-based scans was relatively low across the wide range of scans that we made. During our search through the data, the highest resolution we were able to identify was 1 cm, and we observed nothing in our data that exceeded those results. In general, most of the data we were able to recover only showed details within the range of 2-3 cm at best, and 4-5 cm on average. In both asphalt and broken concrete, only the very worst damage could be seen with the iPad Pro's sensor. Deep, long cracks are often signs of significant damage in road surfaces but are often less than 1-2 cm in width, and thus were barely visible in our collected data. We had the most success picking up surface details like major potholes or areas with wide cracking between older surfaces and newer patches. Details with more points in the z-axis, such as deep potholes and curbs, could be measured with slightly more consistency and accuracy, but details such as cracks and small, shallow potholes that exist on a relatively flat plane were significantly more difficult to measure reliably.

3.2 Site #2

Misclosure on longer scans added a tremendous amount of error to our scans, and the error propagates as distance and subsequent measurements are made. As we lengthened the extent of our scans with the iPad Pro, it was obvious that the errors propagated to the point of creating multiple different layers of surfaces. Figure 13 shows the details of the iPad scan on site #2.

Figure 13 demonstrates the anomalies that resulted from the iPad sensor data. Essentially, three levels of planes are visual. Anomalies in the curb and gutter are present.

A comparison to the Terrestrial scanner was not necessary because the visual inspection does not remotely represent the road.

Figure 13. Site #2 New Asphalt
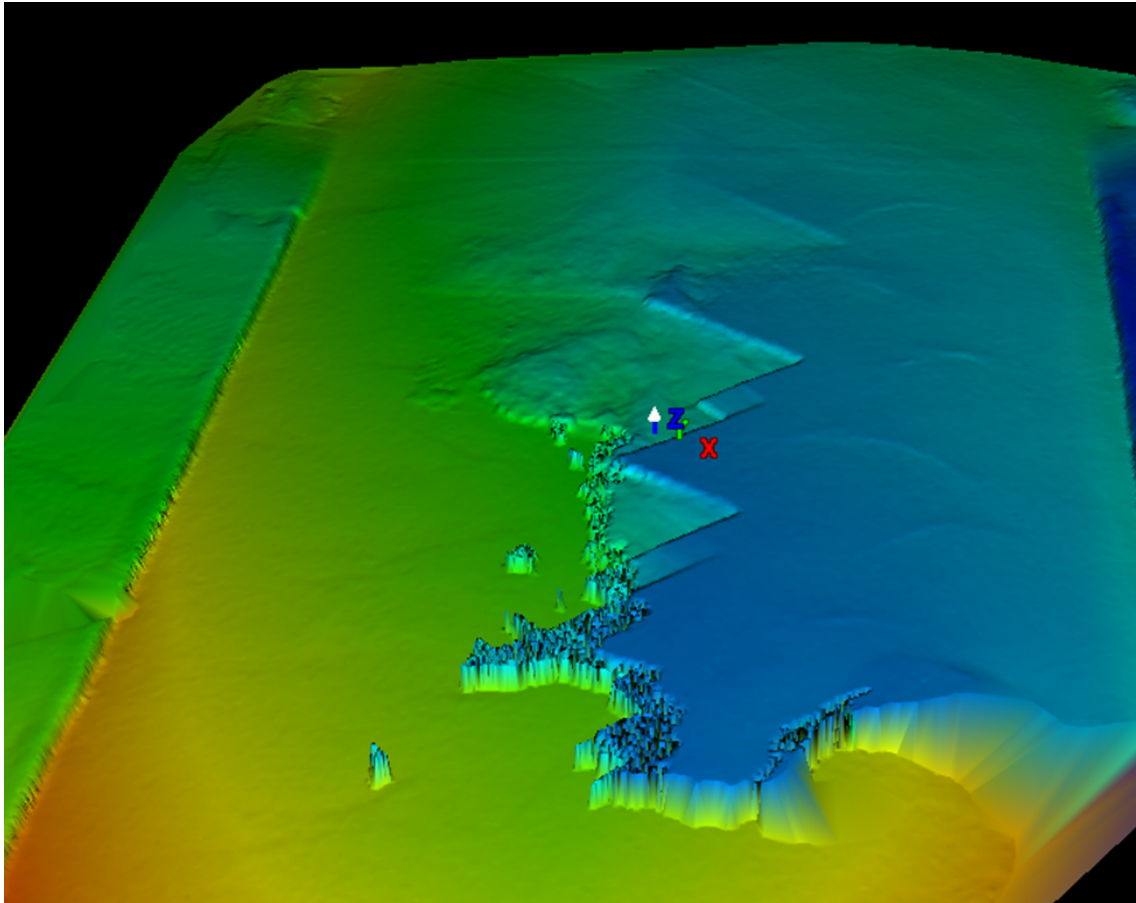
On scans that had ends that were not closed, long, linear images generally appeared to maintain a semblance of linearity. However, on scans that closed back on themselves (a traverse of sorts), it was clear that the data contained an unusable amount of misclosure. Many of our longer scans had overlaps that misclosed as much as 10 cm. The app had no recognition of these misclosures/misalignments and would simply take action to mathematically force the misclosed edges to connect. This meant that the surface models it produced were full of large, geometrically shaped edges where none existed on the physical surfaces. As shown in Figure 14, a cross-section of the derived point cloud shows the vertical misalignment on site #2.
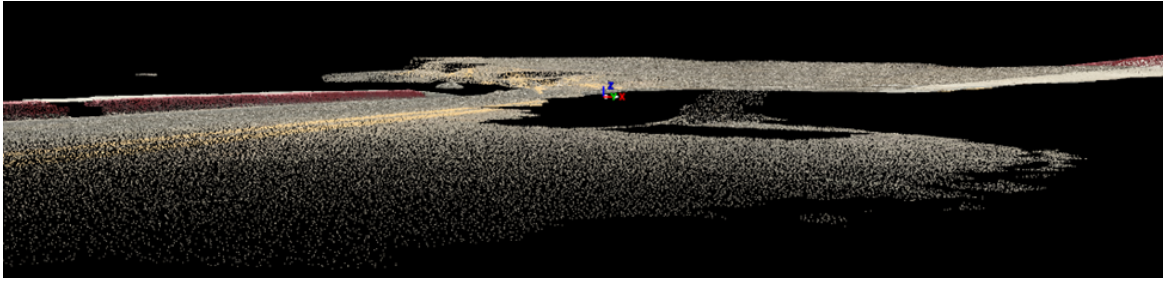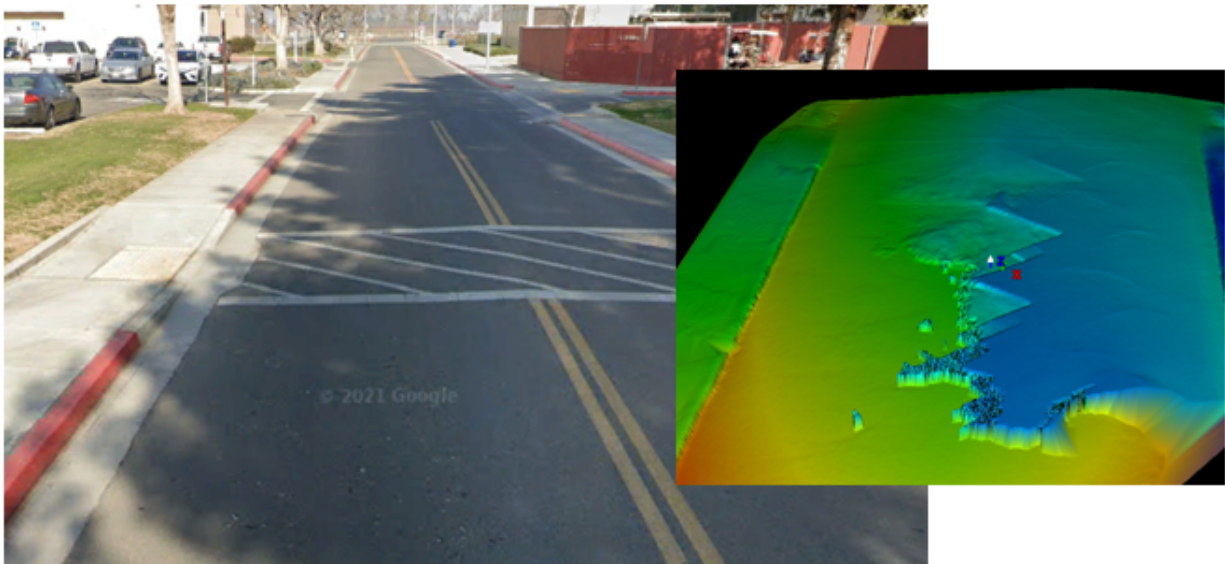
Figure 14. Cross-Section Revealing Vertical Misalignment

Figure 15 compares the picture alongside the LiDAR sensor data.

Figure 15. Site #2 Visual Comparison vs LiDAR Comparison

3.3 Site #3

Site #3 was a concrete surface. As mentioned earlier, it has obvious visual deformation and cracking. The concrete shows evidence of roughness, joint/crack deterioration, surface defects, and grading misalignment (Figure 16).

One slight area of success was using the iPad Pro data in a colorized format. A surface model could not be used to extract valuable data. The resultant surface showed only a smooth finish. No cracking, deformation, or grade changes were present in the derived surface from the iPad data. However, when viewing the points using their true color, contrasting colors would show damage on moderately damaged surfaces. It does create a form of visual inspection, but it is no different from what a digital camera can provide. Cracks in the surface of the concrete were too insignificant

to be visible in the iPad Pro LiDAR data, but light and fine cracking was still invisible in these colorized scans.

Figure 16. Colorized Point Cloud of Site #3

3.4 Potential Sources of Error

The novelty of using an off-the-shelf device without calibration and proper site control is considerable. Unfortunately, there are too many potential sources of error with this method to identify any one main source. The first potential source we found was the Inertial Measurement Unit (IMU). The IMU is a chip within the architecture of the iPad Pro that allows the device to know where it is in 3D space. It does this by taking thousands of inertial measurements as the device is moved in six axes. The device's ability to compute its location as it is being moved is critical for establishing the readings being taken by the LiDAR sensor on the device. If the IMU is not taking measurements quickly or accurately enough, this will affect the output data.

The second potential source of error is the LiDAR sensor itself. The sensor is not particularly accurate on the scales we need for crack detection and is also highly susceptible to bad readings from objects that have poor emissivity. While we could not find exact specifications for the sensor from Apple, we can safely assume that the number of measurements per second is at least several orders of magnitude less than that of a professional-grade scanner. We also noticed that what seemed to affect the areas of poor emissivity the most was the actual texture of the surface more so than the color of the material. Sand and gravel in the bottom of a pothole typically were not

measured accurately, even though that mixture was composed of materials that normally have good emissivity.

Lastly, as we are unable to see how the onboard processing of the data within the 3D Scanner App is performed, we can also regard this as a potential source of error. Essentially, the data processing operates as a black box, and without writing our own software, we cannot confirm that the best practices are being used to catalog and process the data coming from the sensor.

4. Future Potential

4.1 Gimbal Stabilization

In the future, a gimbal stabilizer may be used to increase the quality of scans being produced. Others have demonstrated that, with the addition of a gimbal stabilizer, such as the ones sold by DJI, Inc for photography purposes, data can be produced using the iPhone, which carries the same sensor on board and has less misclosure over long, linear measurements (Tamimi, 2022)(Tamimi, 2022). The gimbal stabilizer is intended to smooth the transitions in 3D space between the individual measurements of the IMU, allowing the raw data being collected to be less jerky and therefore more accurate.

4.2 Processing Raw Data

We hypothesize that the 3D Scanner App is not processing data in the most accurate, rigorous, and processor-intensive way, since the app is designed to run on an iPhone 12, the least powerful Apple product to carry this sensor. If we were to obtain the raw, unfiltered measurement data directly from the sensor, we assume that we could use more intensive and accurate PC-based processes to process our data. If an app could be written to do this, the final deliverable would be an improvement over its current capabilities.

4.3 Hardware

As companies like Meta continue to advocate for products like the Metaverse and other companies continue to leverage Augmented Reality (AR) in their products, we can assume (or perhaps hope) that Apple will continue to improve the sensor installed on their products. The LiDAR sensor is the physical method by which the digital AR world on a device is linked to actual 3D space. Making this link more robust and accurate while improving the speed and accuracy of the IMU would improve the ability of Apple products to use AR and, by extension, would bring this project closer to a productive solution rather than leave the deliverable lacking. This will likely occur in the future, but we cannot know for sure.

4.4 Setting Control

The use of physical control points in the scanned area would considerably increase the quality of the scans, particularly if the raw data could be obtained. Being able to measure markers and their relationships to each other with the precision needed, however, would dramatically increase the cost of each scan. A total station of high accuracy would be needed, as well as an experienced technician to operate it and perform the scans. However, the cost of this approach would exceed half of the price of using a scanning total station or even a laser scanner like the Leica P20 used in this project. While the deliverable would be greatly improved, this method would still not have the

necessary resolution to display the types of cracks we aim to measure, and it would be expensive, negating the purpose of the study altogether.

Conclusion

After various tests, adjustments to processing, and variation in the collection methodology, we have determined that the Apple iPad Pro cannot be used to collect and categorize the necessary information needed to assess roadway surface damage. From the three surfaces tested in this study, which involved differing degrees of pavement condition, none of the surfaces produced usable or reliable data. Smaller deviations in cracks and holes in the asphalt were not detectable, while large areas produced vertical misalignments, thus obscuring which data were reliable and usable.

As discussed in Section 4, there are several sources of data that can be tested to isolate any potential systematic issues. However, given the vast number of roads of carrying conditions in California, inspections by sight and camera still produce better and faster results than what the iPad and iPhone LiDAR sensor can currently yield.

Currently, it is recommended that traditional LiDAR scanning and visual inspection continue until other means and methods are further developed.

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