Mobile phone based laser scanning as a low-cost alternative for multidisciplinary data collection

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Airborne and terrestrial laser scanners have traditionally been used as specialised toolsets for three-dimensional scene capture in engineering, providing highly accurate measurements with increasingly minimal human interaction. However, commercial or engineering-grade scanning instruments remain expensive and sensitive, requiring costly routine calibrations to ensure their optimum functionality. The recent inclusion of laser scanning sensors by mobile phone corporations such as Apple Computer Inc. is now analogous to the integration of Global Navigation Satellite Systems (GNSS) and cameras into smartphones as seen decades ago. Likely, these initial efforts to include the scanning sensor in mobile phones will see rapid improvements in the application and accuracy of the sensor to serve the growing need for scanning applications for transdisciplinary users. However, there is a limited amount of literature that benchmarks the emerging and low-cost scanning sensors to existing commercial ones to inform practice, thus prompting a need for researchers to evaluate and provide scientific evidence that can inform multidisciplinary scanning. It was noted that there was some absolute positional shift and scan drift in the iPhone Light Detection and Ranging (LiDAR) data. The researchers therefore investigated the extent to which the accuracy of laser scanning tools available within the iPhone 12 Pro compared to engineering-grade laser scanners. Outcomes from the study showed that iPhone scanners can deliver the required models, despite being unstable in dynamic environments when pitched against engineering-grade LiDAR scanners. The research recommends that stabilisers, such as stabilising gimbals or enhanced GNSS receivers, be used in practice to achieve improved accuracy from the mobile phone LiDAR.

Significance:

Laser scanners offer multiple advantages for modelling features in three dimensions in diverse applications, including documentation, archaeology, environmental modelling and mapping. However, the cost of entry to acquire scan data has been a limitation to its wide-scale use across multiple disciplines. This study demonstrated from an accuracy-based perspective that iPhone scanners can deliver the required models addressing different model purposes, despite being slightly unstable when pitched against engineering-grade Light Detection and Ranging (LiDAR) scanners. The results are significant in reinforcing the competence of low-cost tools in increasing access and use of this technology in curating three-dimensional models for multidisciplinary work.

Introduction, background and aims

Light Detection and Ranging (LiDAR) scanning systems allow users to create observations of any human-constructed or environmental structures for application in hundreds of areas such as geology, real estate, heritage, archaeology, deformation monitoring, engineering and other precise spatial data collection.[1,2] Scanning approaches a broad spectrum of users across the technical context of aerial (ALS), mobile (MLS) and terrestrial laser scanning (TLS) applications.[1-3] These scanning applications (which can be airborne, mobile or terrestrial) are known to provide quick and accurate multi-point positional data, which are currently collected at increasingly faster rates.[1,3] Furthermore, terrestrial laser scanning, in particular, employs the use of high-grade equipment capable of providing excessively large volumes of point cloud data with detailing for topographic mapping, meteorology, archaeology, deformation monitoring, construction and mechanical structure analysis in engineering.[1,3] This diverse range of applications has also been met by rapid hardware developments and processing capabilities, with technology developers attempting to make their offerings more accurate, more efficient and more affordable to a larger market.[4,5] Recent applications have also extended to include human and social sciences as well as arts where physical models are now increasingly of interest.[5-7] Typical examples include metrology, health sciences, development studies, forensics, biodiversity and many others. However, despite increased awareness and the need for scan technology, actual access to scanning services has remained a barrier to its full-scale or broad application due to the prohibitive costs associated with commercial scan equipment and its maintenance plans.[8,9]

On the contrary, since 2007, when the first iPhone was announced, the world has seen a rise in related high-end mobile phone interfaces that have claimed to revolutionise many professional disciplines, by offering mass integration of distinguishable technologies with varied purposes, into mobile devices.[5] This is also the case in other markets, including Android-based technologies and other smartphones across the market. The particular rise in popularity of Apple Computer Inc.'s iPhone is driven by the corporation's constant innovations and out-of-the-box utilities.[10] More recently, Apple Computer Inc.'s ambition to improve its presence led to the inclusion of their first-generation LiDAR (hereinafter referred to as iLiDAR) sensor incorporated into their new iPad Pro and iPhone 12 Pro models and successive devices beyond, up to the more recent iPhone 15 range.[10-12] The incorporation of the LiDAR sensor into the iPhone was intended to improve their measure application (app) capabilities by introducing depth sensing, portrait image capability, night mode performance and augmented and virtual video game functionality.[8] The iPhone 12 Pro and later models cost above (approximately) ZAR30 000, and now provide LiDAR capabilities to the public, marketed to provide real-time processing ability leading to comparable results, at no routine scanner maintenance fee. This package presents an incredible opportunity for a broader application base at the hands of the market base. It is therefore scientifically interesting to benchmark these lower-cost laser scanners (e.g. iLiDAR) or sensors to engineering-grade technologies. Engineering-grade laser scanners are high-end specialised instruments known to obtain accurate spatial data effectively and accurately. However, their cost and application in less precise work is a barrier to adoption as they can range between ZAR600 000 and ZAR2 000 000, making them ideal investments for large projects and precise data programmes. Moreover, they require routine calibration and maintenance to ensure they satisfactorily deliver on accuracy over time.[6] Literature posits that there is insufficient documented knowledge on the iLiDAR capabilities, as there are very few studies that have captured the gains of this recent development from a scientific perspective.[13-15] The problem therefore lies in the limited amount of literature that benchmarks the emerging and low-cost LiDAR sensors to existing engineering-grade or commercial ones to inform multidisciplinary practice. Thus, this presents a knowledge gap for researchers to respond to, providing robust evidence that can assist users who may need to utilise mobile scan technology for diverse applications. This paper adopts a positivist paradigm and aims to test the accuracy of the iLiDAR sensor and its capabilities in generating a terrestrial laser scanner-derived point cloud by evaluating it against engineering-grade data collection sets. The research design is formulated to investigate the extent to which iLiDAR tools are available within the iPhone 12 Pro, compared to the engineering-grade laser scanner in terms of positioning, processing and visualisation. Monitoring how different technologies are being incorporated into mainstream technologies and how fast they grow in complexity will give an insight into the current accuracies and inform future data collection paradigms.

Associated theories and related literature

The measurement principles behind LiDAR scanning juxtapose the numerous benefits and applications of the technology, sharing a similar base concept of electronic distance measurements, which is now widely and at times passively used.[1] LiDAR at its core is a range detection method that uses a laser pulse to illuminate an object and measures the time taken for this pulse to return to the source, allowing the LiDAR scanner to accurately measure the distance between the sensor and the object.[3-5] From the interaction of the laser pulse with an environment, a three-dimensional (3D) impression of the real world is recreated with a collection of X, Y and Z coordinates for multiple locations. LiDAR sensing under low light conditions provides overall accuracies of 0.191 metres (m), 0.242 m and 0.345 m at 20 m, 40 m and 60 m altitudes.[6,7] Commercial terrestrial and mobile can achieve an accuracy of less than 20 millimetres (mm) for time-of-flight (TOF) scanners and less than 10 mm for phase difference scanners.[7] It should be noted that this is a very general estimate due to the wide range of LiDAR scanners available on the market, as many can provide between 3 mm and 6 mm accuracies. Mobile laser scanning takes the concept of terrestrial or ground-based laser scanning by adding real-time kinematic (RTK) GNSS and inertial measurement unit (IMU) systems for a moving platform.[2,7] This allows scanning to take place in rapid succession by driving a LiDAR scanner mounted to a vehicle/platform and producing a geo-referenced point cloud through registration.

Several models and frameworks have been postulated to explain user adoption of new technologies, with more than one theoretical approach required for a complete understanding of the broad trends we may see in technology uptake.[10-13] In this paper, technology adoption theories and models are not primarily significant given the research context. However, due to the practical nature of the findings in a rapidly advancing technological space, which may get dated quickly, there is merit in highlighting that technology adoption theories explain the changes and growth in the development of low-cost devices. In the case of the iLiDAR sensor, the literature articulates that third-party applications (apps) capitalised on the opportunity to use the LiDAR system in conjunction with the processing power of the iPhone's new bionic core, to provide 3D models just as the terrestrial LiDAR systems would.[14,15] The iLiDAR scanner is a combination of model sensors that provide users with the potential to approximate engineering-grade mapping capabilities, as it combines a refined GNSS receiver, enhanced gyroscope and accelerometer sensor as well as what is described as a high-precision camera sensor and LiDAR sensor.[16-19] The resulting 3D models then appealed to multiple disciplines who saw an opportunity to use the iLiDAR for reality capture and documentation. Thus, the additional ability to reconstruct 3D models using the iLiDAR is accredited not to Apple alone, but to several third-party sources who developed these apps to take advantage of the LiDAR system using the app developer's designed algorithm.[20] The sensor functions offer the same scientific concepts as their professional-grade counterparts albeit reduced to the most basic components. The apps can produce well-textured models using a simultaneous localisation and mapping (SLAM) algorithm, which in practice allows for the reconstruction of maps and models through the continuous updating of results using precise resection of the scanner's location and orientation.[21] SLAM is primarily used in mobile laser scanning, as the LiDAR scanner is mounted to some moving platforms or vehicles with the Global Navigation Satellite System (GNSS) and IMU systems constantly keeping track of the vehicle during acquisition. This would occur while the SLAM algorithm allows for registration and geo-referencing of all points in question.[21] Apart from its use in augmented reality and gaming, iLiDAR capabilities are promising for forensics, real estate, physics, archaeology and engineering documentation, as seen in a related study by Luetzenburg et al[14]. in which the accuracy of the iLiDAR systems was quoted to fluctuate between 3 cm and 6 cm.[6,14-17] This range demonstrates a high potential for the mapping of small-scale scenes where absolute positional accuracy may not be required, such as residential rooms and furniture in real estate.[14-16] However, despite these merits, the rapid growth to increase the reach of scan ability and the addition of specialised competencies to the selected mobile phones still demands immense focus to obtain more accurate measurements in real time, bearing in mind that engineering-grade scanners require recalibration to continuously provide quality data.[18,19,22]

Tavani et al.[15] describe the iPhone 12 Pro LiDAR system as a huge paradigm shift, improving the geospatial data acquisition process through acquiring 3D reconstruction models for fieldwork in real time. The study resonates with related works by other scholars and posits that such a capability in the hands of scientists, such as geologists, would improve research fieldwork opportunities by increasing access to low-cost LiDAR data and enhancing repeatability and transparency.[14-16] It is also noted as possible to add location detail or GNSS capability using the iPhone 12 Pro GNSS receiver; however, due to the low resolution available to these sensors, absolute accuracy would not approach engineering-grade standards. However, in a study conducted by Tamimi[17], it was concluded that the use of an external real-time kinematicGNSS receiver connected to the iPhone 12 via Bluetooth may provide much higher accuracy by using much more defined positional information. It is, therefore, one of the objectives of this research to evaluate whether the same is true without the external real-time kinematic receiver, particularly to evaluate if GNSS positions from the built-in receiver aid in any way to the final deliverable. In the same study by Tamimi[17], it was noted that the iLiDAR data accuracy did not increase too significantly between Generation 1 and Generation 2 LiDAR and camera systems. Its relative accuracy was exceptionally low when compared to that of the total station data or in comparison to what can be obtained with engineering-grade scanners, where most results attain less than 10 cm accuracy. According to the numerous studies conducted to compare two-point cloud data sets, including those of Tavani et al.[15] and Chauhan et al.[18], a trend for a defined accuracy assessment procedure that mirrors the one initiated by Parrish et al.[23] is evident. In the work conducted by Parrish et al.[23], the suitability of the iLiDAR sensor for forensic work was interrogated. The researchers used three techniques for LiDAR comparison, including a cloud-to-cloud (C2C) comparison, a rudimentary comparison of tape measurements, and a chalk outline clarity test. Similarly, Chauhan et al.[18] used point cloud comparison across two different registration algorithms. Individual point clouds were aligned together in Cloud Compare and made use of the C2C distance model computations. According to Chauhan et al.[18], 3D deviation analysis between point clouds is best performed using a C2C computation to provide for a comparison of the entire range of available points instead of a point-to-point or point-to-cloud method. In summary, the research cites that four distinct distance models can be used: the C2C comparison, C2C distance, multi-scale model-to-model (M2M) cloud comparison, and model-to-model cloud (M3C2) distance.

Conclusively and based on the literature[18,23,24] LiDAR scans conducted using two different scanning methods can be compared based on the overlap they provide, an estimation of the drift seen in the data and how the data sets manage elevation changes.[25,26] Such a comparison allows researchers to consider diverse data collection paradigms and evaluate how they conduct their work as seen in several studies.[27,28] The current study addresses its objectives by collecting data in the field and adopting a C2C and M3C2 approach in comparing the derived point clouds to take advantage of the statistical robustness of the comparison techniques which makes them robust and scientifically sound in tests.

Study area, materials and methods

The study site selected for this investigation was an old building area within Rondebosch, Cape Town, South Africa. Cape Town is on South Africa's southwestern coast close to the Cape of Good Hope and is the southernmost city on the African continent. The Snape and Menzies buildings[9], which date back to the early 1900s and are located in Rondebosch, Cape Town, were selected as study subjects as they presented regular but moderately complex facets with staircases and corridors that allow for robust testing for the case at hand. Another primary consideration towards the selection of the specific site and buildings was to opt for buildings that had been previously scanned with ease and therefore accommodate that learning to the iPhone 12 LiDAR scanner to mitigate any limitations it may face about the uncertainties in measuring highly complex structures as similarly proposed in related studies.[30] It is important to highlight for ethical considerations that the authors have obtained ethical clearance to conduct the work and have no conflict of interest or link whatsoever to Apple and its related stakeholders. The iPhone 12 Pro and its selection for the research was based on its availability to work, particularly as one of the few mainstream mobile technologies at present, which have introduced scanning technology. The researchers reflected on the overall research design to ensure that selected methods and data collection approaches would be optimal for the analysis. The initial fieldwork step was to set up ground control points (GCPs) of known geographic positions established using a highly accurate static GNSS approach as control data for the experiments. In establishing the control network, it was important to reflect on the intended provisional scan position to ensure that there would be enough control data in the system to cover the entire building with minimal error and an efficient geo-referencing of scans. Scanner setup positions were selected based on the amount of detail per area and the intent to introduce overlap between scans within proximity to the available ground control points. Two additional ground control points were placed outside the main test site and observed using virtual reference station real-time kinematic (VRS RTK) GNSS due to limited nearby control and a decline in satellite lock for GNSS reliability in densely built-up areas. As highlighted in the introduction, to evaluate the integrity of the iPhone 12 LiDAR scanner, it was to participate as would the engineering-grade scanners, and it was compared to both an X7 Trimble Laser scanner and a Z and F scanner. Using the iLiDAR scanner, the researchers were able to produce a workable deliverable by following a similar workflow to that of mobile laser scanning due to the similarities in the data acquisition process. To make room to register successive LiDAR point clouds, targets were placed on the walls wherever possible. These targets were black and white markers and were placed about 1.5 m above the ground. They were not placed throughout the site completely, because of weather conditions during fieldwork. In some places where markers could not be placed, noticeable features like the edges of clearly defined signs for the remaining segments of the building were identified and noted as useful. The iLiDAR, Z and F and the Trimble X7 (TLS) scanner were deployed, and point cloud data were collected. Because the iPhone LiDAR needed to be on the same coordinate system as the laser point clouds from engineering-grade scanners for comparison and to maintain good positional accuracy for the iPhone during data capture, open-source GNSS data were used. The iLiDAR data preparation included a registration step as the scanning process was done per wall to reduce strain on the iPhone processing unit. Each data bundle allowed for a C2C registration done in the field, where it was noted that the relationship between scans and ground control points was not as vital for registration and transformation, as in other scanning approaches. Thereafter, cleaning of the merged data bundles was done to remove all unnecessary features from the point cloud such that only the building features, paths and steps were accounted for. This was to ensure that the iLiDAR point cloud has similar details to the engineering grade data sets to enable a correct comparison between any two data sets. Once the data were ready, the phone scan data were compared to the engineering-grade point cloud to highlight similarities and key differences. An accuracy-based approach was adopted using algorithms within Cloud Compare using the C2C and M3C2 comparison.

Results and discussion

Using the field data for the iLiDAR scans, we followed a workflow like that of processing mobile laser scanning due to the similarities it holds with the iLiDAR data acquisition process. The cleaning of the collected data, particularly for iLiDaR, involved removing all unnecessary features from the point cloud such that only the building features, paths and steps were accounted for, as shown in Figure 1. This ensured that the precise point cloud had the same features as the engineering-grade LiDAR point cloud and would enable a correct comparison between these two data sets. During the importing process, the iLiDAR point clouds appeared to struggle to be interoperable with the software of choice, and when loaded, the point cloud would either be extremely small or disintegrate into an extensive line of points. A probable reason for this may be due to the processing done by the A14 64-bit ARMv8.5-A system on a bionic chip that may not be allowing the cloud to communicate to the computer correctly or may also deal with the way the iPhone 12 formed the geo-referenced file. This was as expected and seen with many Apple devices, where compatibility with other platforms may not always be smooth, as we see in related work by Allen et al.[27] and Liu et al.[30]

After cleaning, some further inspection of the data followed. Another challenge identified was that where the iLiDAR would only have minimal overlap areas at the edges for each wall, a least square adjustment matching solution would cause walls to be inverted in the opposite direction. This was attributed to the matching algorithm that views the maximum amount of area within the scan overlap region by tying in other similar features to one another. However, this caused the scans to be mirrored to one another so that the faces of the features overlapped

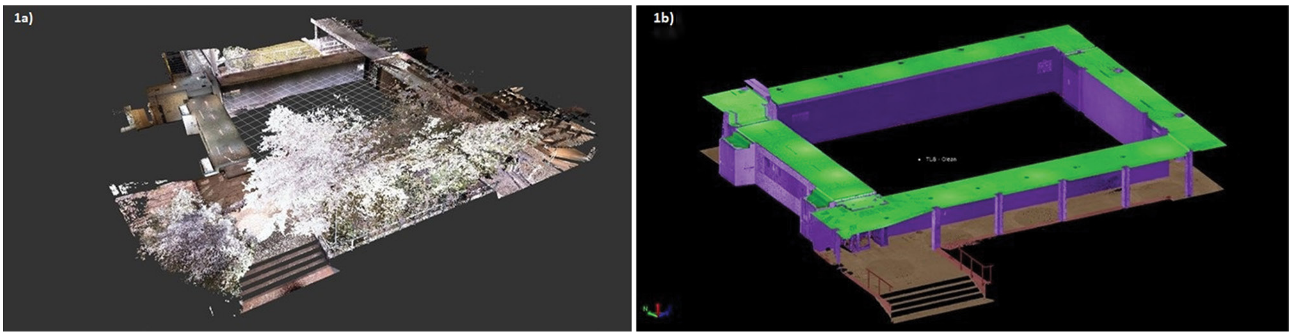

Figure 1: (a) Uncleaned Trimble laser scanner (TLS) point cloud; (b) cleaned and classified TLS point cloud.

on top of one another orientated in the same direction. This could be resolved with an additional point at the end of the wall to keep the orientation of each scan defined. Resolving this challenge meant that the iLiDAR scans now had to be aligned to the Trimble laser scanner and Z and F data set using an iterative closest point-based rotate or align function. It was finely aligned using the Finely Align function to correct for the remaining orientation discrepancies and overlay the two scans together. This effectively registered any two clouds together. In the case of TLS cloud, for example, this was achieved after 20 iterations and 5000 random point samplings (Figure 2).

The aligned scans merged into a one-point coherent cloud for both 2 m and 4 m scans. The 4 m scan contained the inside corridor. Because the inside corridor needed enough points to tie the scan into the remaining other scans, it was integrated into the 4 m scan. Although the scan could not have been done with a 4 m scan range, this choice is justifiable as scanning was done using the maximum possible distance away from the object. These merged scans were exported to Trimble Business Centre (TBC) to be classified and cleaned further. The accuracy of the iLiDAR point cloud could now be evaluated further by the researchers, using visual interpretation, C2C and M3C2 distance models as adopted from the literature. These compute metrics based on the distance between two respective points in a point cloud. The cloud distance methods, the detection and removal of outliers were facilitated using a Python programme. The results are summarised in Table 1 to highlight the change in centrality for each local model, providing insight into the skewness, concentration and distribution of the data. Visual analysis of these data was summarised in descriptive statistics tables which gave an overall mean and 95% confidence interval for each scan. The products of the M3C2 distance algorithms were also provided with their corresponding tabulations and heat maps concerning the C2C distance method. The M3C2 provided distance comparisons and summaries for its cloud distance computations and an analysis of the statistical models used for conveying the product's precision. Table 1 shows the descriptive statistics of each C2C local model distance in 2 m scans. The removal of outliers using percentiles caused a change in accuracy of 1.3 cm, indicating that these are groups of large values, up to 60 cm, in small proportions, implying that potential outliers were removed. Evaluating the data across all the local models revealed that the relative accuracy of the iLiDAR was between 6 cm and 8 cm, on average.

All models showed low variability with a standard deviation (SD) fluctuating between 5.5 and 7, and standard error measures close to zero, implying that these averages are good estimators of the true mean. In addition, the 95% confidence interval in each model allowed for a 3 mm window for its estimation of the true mean, implying strongly that these means closely approximate this value. The final outputs of each C2C distance local model used in the iLiDAR comparison for the 2 m scan were also prepared with its scalar field colour ramp, as illustrated in Figure 3, showing the colour corresponding to the distance calculated and a 10 m scale bar. The data set showed the visual distributions of the departures across the object surface, revealing the areas demonstrating the most and least variation from the TLS data set. Red regions on heat maps remained consistent between all local models; however, some models are more lenient with reporting the effect these areas have on the data. The red areas within the nearest neighbour (NN) and two-dimensional triangulation (2DT) models have more missing data in these regions, which indicates that these are the locations where most outliers were removed. The converse also remains true regarding blue areas, showing very stable results across all models having very dense point counts and showing extraordinarily slight variation across all models, such as the west wall. Areas of interest regarding larger error values include the north (front-facing wall) entrance and its adjacent wall segments. These areas of interest appear more speckled in the least squares plane (LSP) and quadratics height function (QHF) models with very random error responses ranging from exceptionally large, 22 cm, and exceedingly small, close to zero.

From the results of the above methodology, we aimed to evaluate whether the factors of our initial view on the comparison of accuracies of iLiDAR with commercial scanners would coincide with what we observed in the field. A C2C and M3C2 distance assessment provided an approximation of the iLiDAR accuracy using descriptive statistics providing different averages for the distance discrepancies, giving a general idea of what the system can give under a 95% confidence. In addition, the use of the root-mean-square (RMS) and Chi-squared results gives a final estimate of the average error observed and shows how well the data can be modelled. The results provided a comparison of distances across the 2 m and 4 m data sets to evaluate if the scanning method yields contrary results to the view or reasserts them. Upon visual inspection of the cloud data sets, all point clouds showed significant departures and large segments of discontinuity in the iLiDAR clouds. However, as a general summary, the iLiDAR seemed to approximate the TLS data set well, specifically within the 4 m scan of the data in the negative direction and represented points behind the wall which could not have been possible. This gave more credence that the lenient local models that produce more noise are utilising erroneous inclusions in their computations. For each local model, the data conveyed that the best estimate of the mean using that algorithm is only 1 mm different from the true mean. This did not imply that the population mean for the iLiDAR scan was 1 mm away from these estimates, but it reported on the confidence we have in the mean computed for that specific algorithm. As the 4 m scan outperformed the 2 m in this manner, it implied that the 4 m provides the more authentic estimation of the accuracy available to the iLiDAR. This was further seen by considering the descriptive statistics tables to their Weibull distribution, where beta values, *b*, decreased from about 0.8–0.6 to 0.33–0.26, which meant that there was more conformity in terms of a lack of reliability to reach the larger error values in the 4 m scan than in the 2 m. Within the 2 m scan, it was noted that due to this, the noisier local models had to come into further evaluation because it was known that it is wrong to assume lower reliability to reach larger values in these areas as we know that the iLiDAR skewed because of drift. However, in the 4 m scan, there was more agreement between the models, and although the reliability on achieving larger values decreased, there was more trust in this assessment and we observed fewer drift errors (see Figure 4).

In addition, because of the scale and shift parameters, it was seen that the reliability was more defined over its error classes, which implies that the Weibull distribution is reporting on the full scope of the errors possible and not understating the effect of the larger errors. It must also be noted that the minimum value for each local model is not exactly zero, meaning

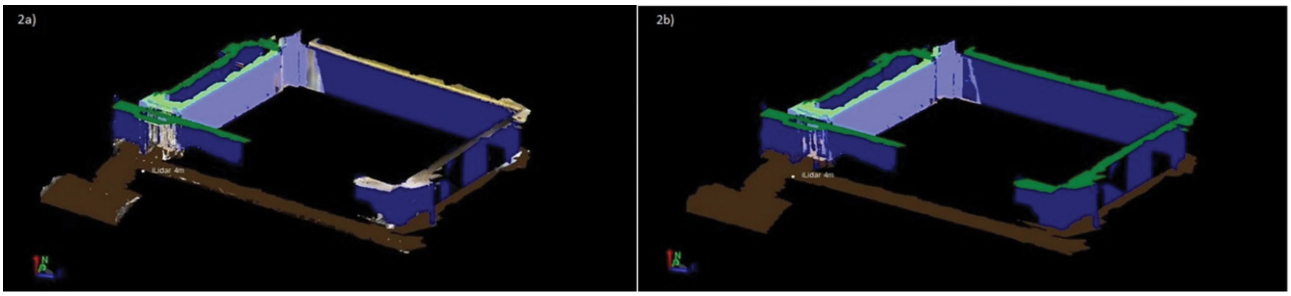

Figure 2: Images of (a) iLiDAR and (b) TLS point cloud alignment and cloud registration in Cloud Compare for 4 m scan.

Table 1: Summary statistics of C2C distance local model (iLiDAR 2 m)

Nearest neighbour		Least squares plan	E	2D1/2 Triangulation	N	Quadratic height function	
Mean (m)	0.080	Mean (m)	0.060	Mean (m)	0.080	Mean (m)	0.061
Standard error (m)	0.00004	Standard error (m)	0.00003	Standard error (m)	0.00004	Standard error (m)	0.00003
Mode (m)	0.003	Mode (m)	0.001	Mode (m)	0.003	Mode (m)	0.002
Median (m)	0.060	Median (m)	0.043	Median (m)	0.060	Median (m)	0.041
Standard deviation (m)	0.070	Standard deviation (m)	0.055	Standard deviation (m)	0.070	Standard deviation (m)	0.057
Sample variance (m)	0.005	Sample variance (m)	0.003	Sample variance (m)	0.005	Sample variance (m)	0.003
Range (m)	0.314	Range (m)	0.228	Range (m)	0.314	Range (m)	0.233
Maximum (m)	0.314	Maximum (m)	0.228	Maximum (m)	0.314	Maximum (m)	0.233
Minimum (m)	0.000	Minimum (m)	0.000	Minimum (m)	0.000	Minimum (m)	0.000
Points	3 131 245	Points	3 165 355	Points	3 129 841	Points	3 160 523
Sum (m)	250 782.6	Sum (m)	190 980.5	Sum (m)	250 440.5	Sum (m)	191 504.1
Classes	1770	Classes	1780	Classes	1770	Classes	1778
Confidence interval (CI) (95%)							
Lower CI (m)	0.079	Lower CI (m)	0.059	Lower CI (m)	0.078	Lower CI (m)	0.059
Upper CI (m)	0.082	Upper CI (m)	0.062	Upper CI (m)	0.082	Upper CI (m)	0.062

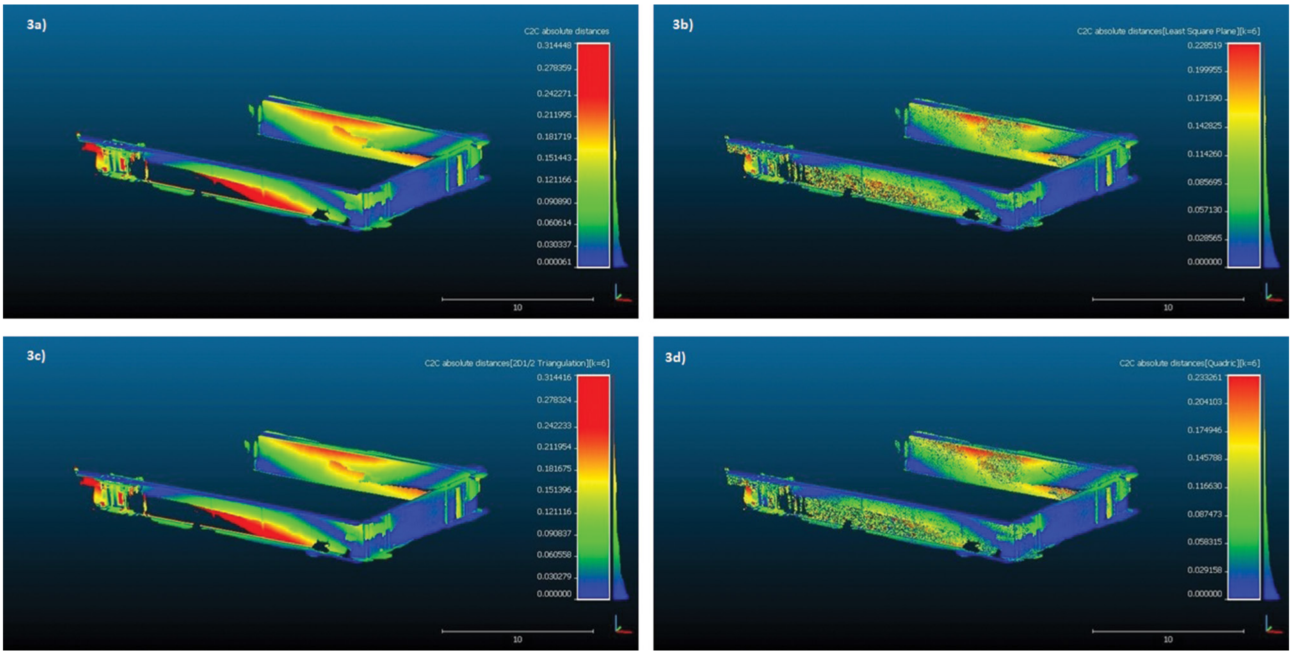

Figure 3: (a) C2C distance – nearest neighbour for 2 m scan; (b) C2C distance – least squares plane for 2 m scan; (c) C2C distance – two-dimensional (2D) half (½) triangulation for 2m scan; (d) C2C distance – quadratic height function for 2 m scan with its scalar field ramp, scale bar and orthogonal axes.

that the iLiDAR is not precisely synchronous with the TLS data set but that based on the local model used, it very closely approximates our TLS in these areas. This was seen as we expanded the values to further decimal places and saw the residual error in the iLiDAR measurements. However, these small errors were sub-millimetre and are not measurable to an exact value in practice. Based on data, long scan lines only increased the chance of misalignment due to drift. A possible reason for this relation between the scan length and misalignment was due to a decreased potential for overlap during the scanning process as longer scan lines make the iLiDAR scan more dependent on maintaining good IMU capability, that is, longer scan lines needed a very good fix on its orientation and position in space than shorter scans, in addition to less available area for overlap. It must be carefully noted that it is a lack of overlap in conjunction with the limited IMU ability of the iPhone that produces these errors. This is reciprocated in the areas within the 4 m scan which had shorter scan lines but much more stable deliverables. Because a 4 m scan will have a larger scope of the object being scanned, there will be a greater opportunity for overlap. This was therefore the primary reason that the 2 m scan failed to reach higher accuracies in comparison to the 4 m scan. However, the iLiDAR point accuracy remains satisfying at < 1 cm at points close to the start as advertised, as there still exists the same drift as the iPhone 12, which makes it incompatible and insufficient for mapping and even dangerous. To that point, however, we can supplement the iPhone data with correctly surveyed control points; we can reduce this error such that one could

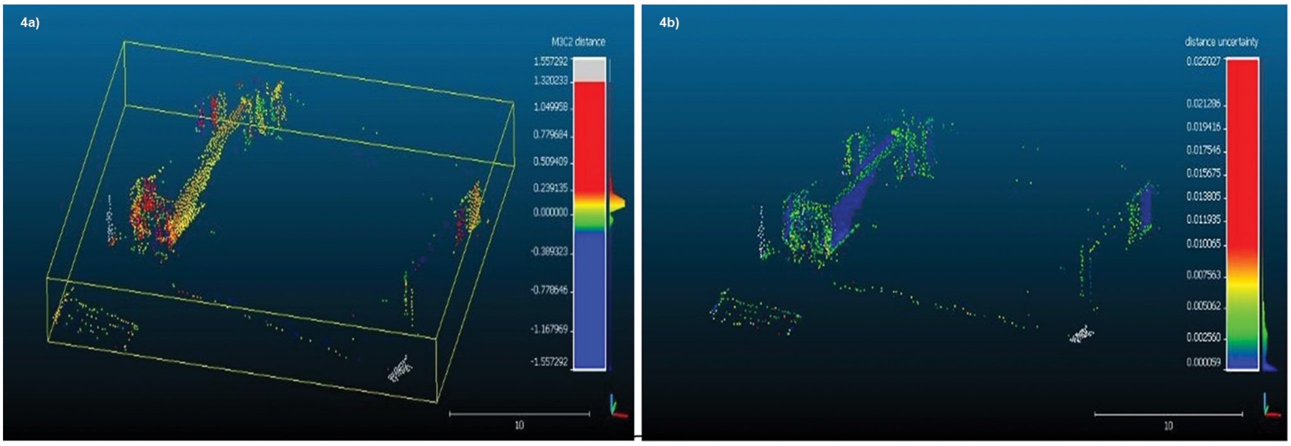

Figure 4: Illustration of where differences or errors lay in the 2 m scan labelled (a) and 4 m labelled (b) (blue region shows the M3C2 distance, low uncertainty ranging through green, yellow, and orange, while red regions are high uncertainty and high M3C2 distances).

say it is relatively accurate if we understand what the results should be. The iPhone 13, a later model than the iPhone 12, does hold its positional accuracy overall, and its colourised points line up neatly with the point cloud.

Conclusions and recommendations

This study aimed to test the accuracy of the iLiDAR sensor and its capabilities in generating a terrestrial laser scanner-derived point cloud by benchmarking it to a terrestrial scanner cloud. The above results indicate that the iLiDAR performed well in the context of a fit-for-purpose tool as seen in the 4 m scans. The same can be observed in the 2 m scans. However, it can be noted that for positional accuracy in cases where highly accurate positional detail is of importance, its inbuilt GNSS capability struggled to provide adequate absolute accuracy as anticipated. This did not aid much, if at all, in maintaining good iLiDAR measurement capability, much as has been seen in mobile laser scanning. To address this, mitigation methods of providing optimal results from the iLiDAR system strongly recommended that a proper stabiliser be used for the acquisition of the iLiDAR if greater accuracy is desired. This would allow the IMU capabilities of the iPhone to work optimally with the SLAM algorithm, and, in addition, the set-up may also benefit from connecting an external GNSS receiver as seen in Tamimi[17]. We also recommend further research towards more integrated approaches with structures from motion photogrammetry to deliver textured models to users and reinforce the limitations of the iLiDAR system which may provide the near 1 cm accuracy cited by Apple developers and Luetzenburg et al.[14].

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Data availability

The data supporting the results of this study are available upon request to the corresponding author.

Declarations

We have no competing interests to declare. We declare that artificial intelligence (AI) was not utilised in the study or in the writing of the manuscript.

Authors' contributions

K.J.J.: Conceptualisation, data collection, data analysis, writing – the initial draft. M.S.: Project leadership, student supervision, writing – the initial draft, writing – revisions. Both authors read and approved the final manuscript.

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