The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-G-2025
ISPRS Geospatial Week 2025 “Photogrammetry & Remote Sensing for a Better Tomorrow…”, 6–11 April 2025, Dubai, UAE

# Uncertainty-aware Evaluation and Fusion of Point Clouds for Simultaneous Scanning of Two State-of-the-art Indoor MLS Systems

Ziyang Xu[1], Simon Fischer[1], Christoph Holst[1]

[1]Chair of Engineering Geodesy, Technical University of Munich, 80333 Munich, Germany - (ziyang.xu, sj.fischer, christoph.holst)@tum.de

**Keywords:** Mobile Laser Scanning, Quality Assessment, SLAM, Point Cloud.

**Abstract**

In recent years, Mobile Laser Scanning (MLS) systems have garnered increasing attention for their efficient and convenient data acquisition, finding widespread applications across various fields. However, most users typically select a single system that best suits their needs, with few attempts to utilize two independent MLS systems simultaneously. To explore this possibility, we selected two currently leading commercial MLS systems (Z+F FlexScan 22 and Leica BLK ARC) and developed an uncertainty analysis workflow to quantitatively evaluate their respective uncertainties. Following this, a trajectory-based fusion method was employed to merge point clouds from both systems. The experimental results demonstrate that our uncertainty-aware evaluation and fusion solution successfully decreased trajectory estimation drift and point cloud noise, offering a feasible solution for evaluation and fusion of simultaneous scanning with dual indoor MLS systems.

## 1. Introduction

Mobile Laser Scanning (MLS) popularity has been increasing for years, especially for efficient 3D documentation of built environment (Holst et al., 2019, Stenz et al., 2020, Thomson et al., 2013, Kaiser et al., 2022). Over the past several years, various indoor MLS systems have been released, offering a wide range of choices for both professional and non-professional users. These systems mainly used for indoor applications could be roughly classified into handheld, backpack-based, and trolley-based systems depending on mounting platform (Shan and Toth, 2018). Figure 1 illustrates several commercially available state-of-the-art indoor MLS systems.


Figure 1. Part of commercially available state-of-the-art indoor MLS systems.

As a typical multi-sensor system of kinematic measurements, the extensiveness and complexity of error sources dictate that uncertainty evaluation of MLS systems is an essential but challenging problem. It is worth mentioning that compared to the rapid updating of various types of MLS systems mentioned above, not enough investigation has been done to address their uncertainties and possible combinations of dual or multiple systems. In addition, all existing commercially available MLS systems are initially designed to be used as a stand-alone product. This means that during data collection process, users often are assumed to choose the most appropriate system to use. However, the fact is that various MLS systems are different and maybe complementary in terms of accuracy, reliability, size, usability, efficiency, etc. Moreover, MLS systems from different companies often differ in realization of time synchronization, data formats, data structures, post-processing software, etc.

Overall, different MLS systems have their own strengths and weaknesses. Taking Z+F FlexScan 22 from Z+F and Leica BLK ARC from Leica as examples, they are two of the leading MLS systems on the market. Leica BLK ARC is compact and lightweight, meaning it could be used to scan narrow spaces, but the processing process is relatively fixed, leaving limited space for professionals to improve. Z+F FlexScan 22 does not have an advantage in terms of size and weight, but it can make more customized post-processing for professionals and it addresses tasks with higher accuracy demands. In other words, if a small-sized system, represented by Leica BLK ARC, has higher availability to access some narrow spaces that are inaccessible to large-sized systems, a more complete point cloud can be acquired in more complex environments. A medium-sized or large-sized system, represented by Z+F FlexScan 22, may be better in terms of data quality, cannot scan small areas of indoor scenes effectively. Therefore, we formulate the hypothesis that a simultaneous scanning of two MLS systems provides point clouds that are superior in terms of completeness and quality to those only from a single system.

In order to answer this hypothesis, there are two main issues that need to be looked at. The first is how to evaluate uncertainty of two simultaneously scanning MLS systems; the second is how to implement point cloud fusion based on uncertainty performance to maximize the advantages of each respective system. Therefore, this paper consists of two main stages: (1) the evaluation of each single indoor MLS system to decide which one is best, and (2) the actual use of these two systems to acquire and fuse the point clouds.

In this paper, the aforementioned Z+F FlexScan 22 and Leica BLK ARC are taken as research basis. To the best of our knowledge, this is the first paper focusing on a simultaneous scanning, uncertainty evaluation, and fusion of these two leading MLS systems. The main contributions are as follows:

(1) A special trolley-based dual MLS-integrated platform is designed to enable simultaneous scanning and uncertainty evaluation of two MLS systems.

(2) A comprehensive uncertainty evaluation workflow is proposed that provides an objective and complete in-depth analysis of two of the state-of-the-art indoor MLS systems currently available on the market.

(3) A uncertainty-aware solution including drift reduction and denoising for simultaneous scanning and point cloud fusion is introduced, enabling fused point cloud with high quality.

This paper starts with a background introduction on MLS systems uncertainty and fusion followed by a detailed review of related works. Then, the methodology and experiment part regarding evaluation and fusion of two simultaneous scanning MLS systems is discussed. In the end, conclusions followed by an outlook for future work are presented.

## 2. Related Works

Evaluating uncertainty of MLS systems is a vital and fundamental task. In recent years, this topic has received significant attention from researchers worldwide, leading to two main methodological approaches: forward modeling and backward modeling (Shi et al., 2021, Stenz et al., 2020).

As a theory-driven uncertainty evaluation strategy, forward modeling strives to construct as comprehensive and accurate an error model as possible in order to thoroughly quantify the various types of errors in MLS data collection process. In this field, various uncertainty evaluations based on forward modeling have been conducted by incorporating error information from different sensors (Barber et al., 2008, Goel and Lohani, 2015, Stenz et al., 2020, Wujanz et al., 2017). This strategy is theoretically feasible and sounds logical. In fact, accurate and comprehensive variance-covariance propagation and modeling is almost impossible due to a limited understanding of mathematical models and physical mechanisms of various error sources. Theoretical dependence of forward modeling strategy and complexity of MLS system itself severely limit the use of such strategy (Holst and Kuhlmann, 2016, Schmitz et al., 2021, Kerekes and Schwieger, 2020).

In contrast to forward modeling, backward modeling employs a completely different approach. As a data-driven uncertainty evaluation strategy, it avoids the exhaustive task of modeling various error sources. Instead, it relies on reference data with higher accuracy as the foundation for error analysis. The core idea is that, due to superior instruments and meticulous post-processing, the reference point cloud—typically from Terrestrial Laser Scanning (TLS)—can be considered nearly error-free in comparison to MLS point cloud. Consequently, the uncertainty of MLS system is implicitly quantified by analyzing discrepancies between MLS and reference point clouds.

In recent years, various studies have compared the performance of MLS systems with TLS systems, aiming to evaluate the accuracy and limitations of MLS systems in different environments. (Thomson et al., 2013) compared the performance of two MLS systems, Viametris i-MMS (trolley) and CSIRO ZEB1 (handheld), with a terrestrial Faro Focus 3D scanner. They conducted two tests: one is Cloud-to-Cloud (C2C) distances between the MLS and TLS point clouds, the other comparing Building Information Modeling (BIM) geometries, such as hallway dimensions and window sizes.

(Lehtola et al., 2017) conducted a large-scale analysis of various MLS systems, including both commercial and research prototypes, in different environments such as a hallway, parking lot, and industrial hall. They compared the results with TLS data and introduced a new quality assessment metric based on internal geometric characteristics, highlighting differences in performance and precision.

(Tucci et al., 2018) reviewed the performance of handheld systems like the Kaartra Stencil and GeoSlam Zeb-Revo, as well as the Leica Pegasus backpack system. Their analysis compared the data with reference point clouds, examining the effect of loop closures and using multiple comparison techniques, such as C2C and Cloud-to-Feature, to assess the accuracy.

(Nocerino et al., 2017) focused on comparing two MLS systems, GeoSLAM ZEB-REVO and Pegasus Backpack, in both indoor and outdoor environments. (Maboudi et al., 2018) explored different strategies for assessing MLS geometric quality, including C2C comparisons, plane fitting, and model-based evaluations. The study emphasized the importance of addressing measurement noise and the impact of loop closures on accuracy.

(Askar et al., 2023) evaluated the performance of the NavVis VLX 2 in a complex indoor environment. By comparing MLS point cloud with data from a Z+F Imager 5016, the study analyzed the accuracy and measurement noise using C2C distances and Random Sample Consensus (RANSAC) algorithm for feature extraction. The SLAM algorithm’s performance in challenging environments, such as narrow hallways, was also assessed. (Al-Durgham et al., 2021) introduced an automatic accuracy assessment method for Mobile Mapping Systems (MMS), evaluating their performance in large-scale urban environments.

In summary, while many studies have investigated the uncertainty evaluation of various MLS systems, most focus solely on evaluating individual systems or comparisons between multiple systems. They often overlook exploring a new mechanism that enables simultaneous scanning and uncertainty-based fusion of point clouds from multiple systems. We aim to address this gap by employing simultaneous scanning to effectively collect, evaluate, and fuse point clouds from two systems: Z+F FlexScan 22 and Leica BLK ARC. Our proposed workflow quantifies the uncertainty performance of each system and gives a feasible solution for uncertainty-aware fusion.

## 3. Methodology

In this paper, we analyze and evaluate two MLS systems for simultaneous scanning, and explore the feasibility of point cloud fusion derived from a designed dual-MLS integrated platform. Figure 2 provides a detailed illustration of the workflow for evaluating MLS systems and fusing point clouds.

The workflow begins with simultaneously obtained point clouds from both MLS systems based a specially designed platform. Before evaluation, the data undergoes preprocessing to remove erroneous points that could negatively impact the results. Additionally, subsampling is applied to reduce the number of points, aiming to speed up calculations without significantly compromising point cloud quality. Next, an alignment of the point clouds and trajectories is performed to transform all data into a local coordinate system. Once all data are aligned within the same coordinate system, uncertainties are exhaustively analyzed based on several proven methods.

It is worth mentioning that this work focuses more on getting reliable and comprehensive uncertainty evaluation results mainly via already existing methods for two MLS systems rather than inventing new evaluation methods. That is why we chose to use methods that have been proven to be effective to ensure the reliability of the results. Finally, based on the uncertainty performance, a fusion method of two MLS system point clouds that balances quality and completeness is introduced. More details can be seen in the following part.

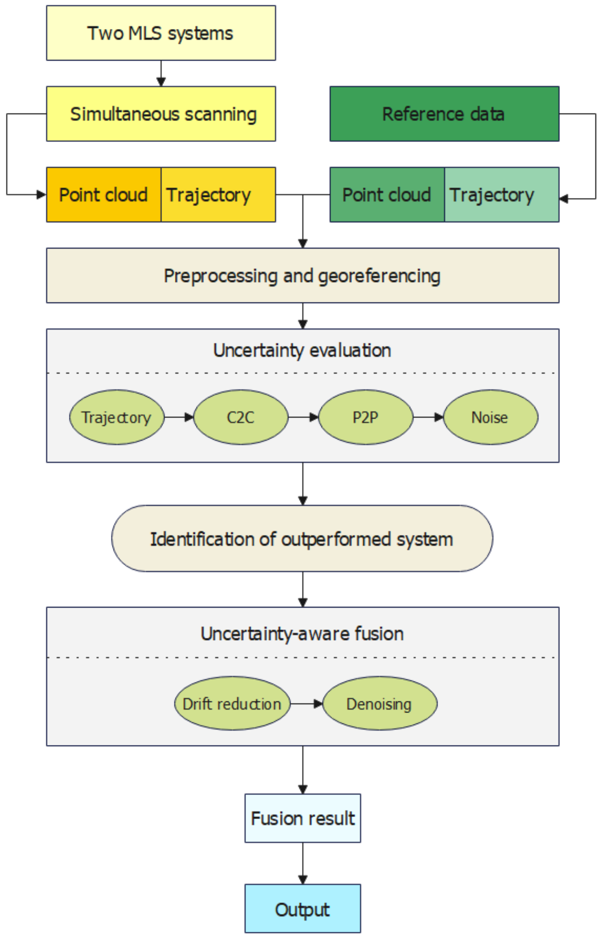


Figure 2. Workflow of uncertainty evaluation and fusion for two MLS systems.

## 3.1 Uncertainty Evaluation

**3.1.1 Trajectory-based Evaluation** As a SLAM-based system, a MLS trajectory visualizes a system's dynamic position movement during map construction. Comparing it with a high-precision reference trajectory, obtained through real-time tracking with a 360° prism and total station, serves as an effective method for uncertainty quantification (Merkle and Reiterer, 2023). The core of this trajectory-based method lies in the construction of point correspondences and the calculation of distances within them. The greater distance between point correspondences represents the higher uncertainty. Ideally, this is a very feasible solution if time of two MLS systems and total station is highly synchronized. However, in our case, time synchronization is basically not feasible. There are two main reasons: (1) Leica BLK ARC does not give any time information and it is not possible to get the timestamp of each track point for users. (2) All these commercial systems use their own built-in time and are not interoperable.

To tackle this, a different method is used, in which the point with the shortest distance in the MLS trajectory is calculated for each point in the reference trajectory. As shown in Figure 3, the method is based exclusively on the calculation of coordinate differences and enables a spatial comparison of the trajectories. In this way the correspondence between each pair of trajectory points can be approximated and constructed.

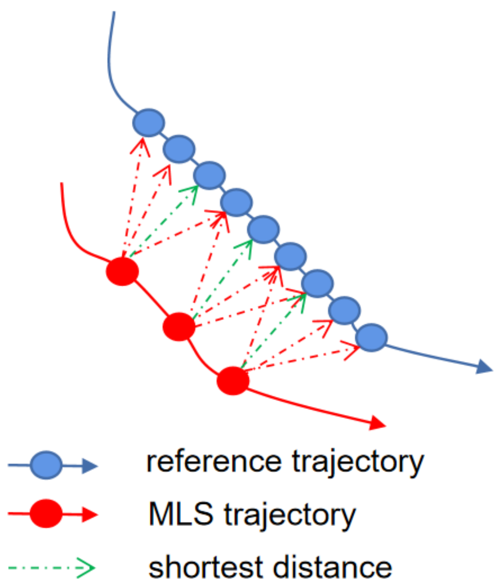


Figure 3. Shortest distance-based MLS trajectory comparison.

**3.1.2 Point Cloud-based Evaluation** In addition to the aforementioned trajectory-based evaluation, more evaluation steps acting directly on the point cloud are proven to be able to quantify the inconsistency of the acquired MLS point cloud with the reference point cloud. Cloud-to-Cloud (C2C) comparison and Point-to-Point (P2P) comparison shall quantify systematic errors, and noise analysis shall quantify random errors.

(1). C2C comparison: To assess uncertainty, two aligned point clouds are required. A high-quality reference point cloud, typically obtained through TLS, is also needed for comparison. The uncertainty is then evaluated by calculating the differences between corresponding points of the MLS and reference point clouds, using the C2C distance (Tsakiri and Anagnostopoulos, 2015).

(2). P2P comparison: This step uses B&W targets as shown in Figure 4 in the scanned areas, which have known coordinates obtained from high-precision tachymetric measurements. These coordinates serve as a reference, as total stations typically have minimal measurement errors. To begin, suitable targets are identified in the point cloud by ensuring their center points are clearly defined and well-covered by data points. The targets should also be evenly distributed across the measurement area for comprehensive analysis. Euclidean distances between the corresponding points are then calculated. This method provides a more precise evaluation compared to C2C distance, as manual point selection reduces errors caused by varying point densities and samplings, which can affect C2C calculations.

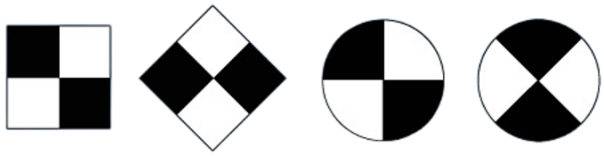

Figure 4. B&W targets used for evaluation.

(3). Noise analysis: Noise in point clouds is analyzed using areas with special geometries, such as walls and circular columns. Planes and cylinders are fitted to these objects directly from the point cloud data. For planar surfaces, a best-fit plane is calculated, while RANSAC algorithm is used for fitting cylinders. These geometric primitives serve as noise-free references. The orthogonal distances between the points and the reference are then measured to determine the noise level, with the standard deviation of these distances quantifying the measurement noise in the data.

### 3.2 Uncertainty-aware Fusion

As we know, Leica BLK ARC and Z+F FlexScan 22 being two different MLS systems, the impact of each error source during data acquisition on the final point cloud is definitely different. In general, simultaneous scanning utilizing these two MLS systems will inevitably result in systematic and random inconsistencies between two final obtained point clouds, mainly reflected in trajectory drifts changing over time and random noise, respectively. Therefore, in order to better fuse point clouds from both, trajectory drift should be reduced and noise should be decreased.

We chose to use the aforementioned uncertainty evaluation as a basis for giving more trust to the point cloud from the system that performs better in the evaluation. This means that the results of uncertainty evaluation are used to identify the outperformed and the underperformed MLS systems, then the outperformed one is used as a reference to minimize systematic inconsistency with the other, as shown in Figure 5. This will allow coverage and completeness of the fused point cloud to be increased while keeping quality as high as possible.

Our segment-wise trajectory-based fusion process involves three main steps. First, after aligning point clouds from both systems (Leica BLK ARC and Z+F FlexScan 22) with their corresponding trajectories during data preprocessing, these point clouds are divided into consecutive segment pairs along the trajectories. Each segment pair consists of data from both systems. In the second step, based on the performance of each system during evaluation, point cloud from the underperformed system is aligned with the outperformed one based on ICP. This alignment helps to fuse two point clouds and minimize trajectory

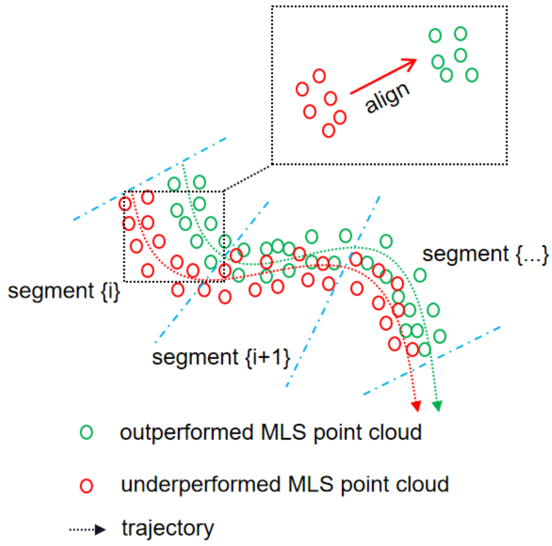


Figure 5. Schematic of segment-wise trajectory-based fusion method.

drift at each segments. Finally, a denoising step based on Moving Least Squares (Alexa et al., 2003) is applied to fused point cloud again to further minimize noise and thus achieve a better fusion performance.

## 4. Experiments and Results

### 4.1 Experiments Design and Data Collection

All experiments are carried out at TUM Geodetic Lab with data collection from a specially designed scanning platform as shown in Figure 6. The platform is equipped with two MLS systems and a 360° prism for trajectory tracking, which provides reliable reference trajectory data. We collected data from a normal indoor scene and a long narrow hallway named Messkeller and Hallway, respectively, as shown in Figure 7. In order to achieve a comprehensive evaluation, we designed 8 test cases, taking into account three factors that may affect final result during data collection and preprocessing. They are trajectory loop, platform moving speed, and alignment strategy.

Here, trajectory loop refers to whether a MLS system's moving trajectory constitutes a closed loop during collecting process. Alignment strategy refers to whether a globally or locally aligned MLS point cloud in prepossessing is used for upcoming evaluation. Globally aligned data means that the entire MLS point cloud is used for alignment with TLS and eventually inconsistencies at different positions will be distributed. A locally aligned point cloud uses only a portion of point cloud from the beginning period for transformation matrix computation, and then applies it to all subsequent point clouds. In the beginning period, our MLS system performs scanning in a static way, it can be seen as drift-free in terms of trajectory as compared to the subsequent periods. Therefore, subsequent trajectory drift can be maximally revealed by this local alignment strategy.

Moreover, in order to explore how these three factors affect uncertainty of two MLS systems, 4 datasets were collected at Messkeller, two of them with trajectory loop closure and the

Figure 6. Designed scanning platform.


Figure 7. Test environment. (MLS trajectories are in red, with pink triangles marking total station positions. In Messkeller, circles represent the starting area (green), ending area with a loop (yellow) or without a loop (red). A blue circle marks a door that determines whether loop closure occurs or not. In Hallway, starting area is green, and ending area is yellow.)

other two without. Another 4 datasets were collected at Hallway without any loop, just with a different moving speed. After data collection, all point clouds were aligned in a global or local way as mentioned before for following up point cloud-based comparison. Reference point clouds and trajectories were collected from TLS (Leica RTC 360) and 3 high-precision total stations, respectively. 49 B&W targets were distributed uniformly throughout the entire test environment.

### 4.2 Evaluation Results

This part mainly shows experimental results for two MLS systems, including trajectory analysis, C2C comparison, P2P comparison, noise analysis.

| System | Scene | Data Set | Max(m) | Mean(m) |
|---|---|---|---|---|
| Z+F FlexScan 22 | M | Loop | 0.083 | 0.016 |
| | | No Loop | 0.097 | 0.019 |
| | H | Normal Speed | 0.108 | 0.010 |
| | | Accelerated Speed | 0.101 | 0.011 |
| Leica BLK ARC | M | Loop | 0.064 | 0.015 |
| | | No Loop | 0.086 | 0.016 |
| | H | Normal Speed | 0.122 | 0.053 |
| | | Accelerated Speed | 0.093 | 0.044 |

Table 1. Trajectory drift results. M and H refer to Messkeller and Hallway, respectively.

According to Table 1, it is clear that both systems have lower maximum drifts in the presence of loops, proving that the availability of loops has a positive effect on decreasing the occurrence of extreme drifts. Based on the mean results, Z+F FlexScan 22 significantly outperforms Leica BLK ARC in trajectory analysis, especially in all Hallway tests, an increase in the mean drift from about 0.01 m to about 0.05 m can be seen.

Based on the C2C comparison shown in Figure 8, cumulative percentage of inliers was calculated, with C2C distances of 0.010 m, 0.025 m, 0.050 m, and 0.100 m marked by grey lines. In the Messkeller, these curves clearly highlight the differences between two systems. For globally aligned data sets, most deviations fall below 0.025 m, whereas this is not the case for locally aligned data. Z+F FlexScan 22 exhibits the highest accuracy, with most deviations being under 0.010 m. For Leica BLK ARC, an improvement due to loop closures is also evident. Z+F FlexScan 22's locally aligned data shows lower deviations compared to Leica BLK ARC.

In the Hallway, similar results to those in the Messkeller are observed. However, the performance gap between Z+F FlexScan 22 and Leica BLK ARC becomes more pronounced, indicating that local alignment is highly effective in highlighting the robustness differences between two systems in challenging environments. Overall, Z+F FlexScan 22 demonstrates superior performance compared to Leica BLK ARC.

Being a long and narrow space, Hallway provides great conditions for detecting changes in the drift between two systems and the reference data during the scanning process. Since the moving trajectory is a one-way straight line, making it challenging for SLAM systems. This setup enables to evaluate which system's robustness is better in terms of continuous trajectory estimation.

As shown in Figure 9, the P2P comparisons highlight the superior performance of Z+F FlexScan 22 in both global and local matching. In global alignment, despite deviations are already relatively uniformly reduced at different locations along scanning direction. Z+F FlexScan 22 still exhibits smaller deviations compared to Leica BLK ARC. In local alignment, the performance gap widens further, with Leica BLK ARC's accumulated deviation near ending point reaching approximately 1 m, significantly larger than that of Z+F FlexScan 22.

Uncertainty can also be evaluated by measuring random noise. As for a plane area, deviations between each point and the best-fit plane could reflect noise level of point cloud. Figure 10

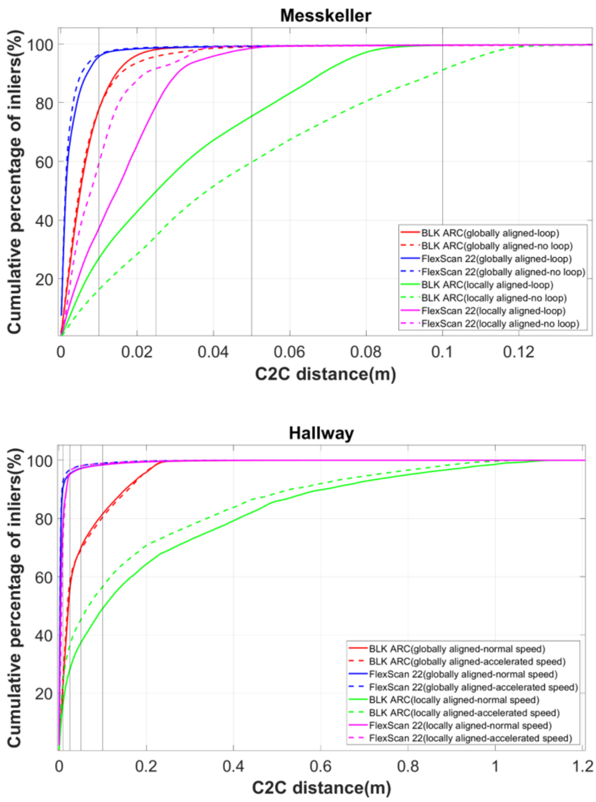


Figure 8. C2C comparison results.

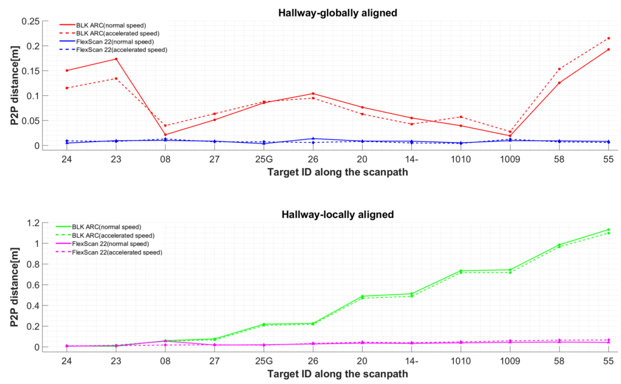


Figure 9. P2P comparison results.

shows that Z+F FlexScan 22 outperforms Leica BLK ARC in terms of random error across walls, floors, ceilings, and cylinders. Its performance is also closely aligned with the reference system, RTC 360. Similar quantitative results can be seen in Table 2, again validating a distinct superiority of Z+F FlexScan 22 over Leica BLK ARC, with a significantly smaller standard deviation.

To summarize, uncertainties of both MLS systems were quantified and analyzed from different perspectives by these previously mentioned evaluation steps. Based on the experiments, Z+F FlexScan 22 shows overall superior results and could be used as reference to perform a fusion of point clouds from both systems in the following part.

Z+F FlexScan 22 is primarily designed for high-precision geodetic applications, which contributes to its higher cost. In contrast, the BLK is also targeted toward non-geodetic users, emphasizing ease of use and efficiency at a lower price point. While both systems serve different purposes effectively, integrating them can complement one another, leading to mutual benefits and improved overall performance.

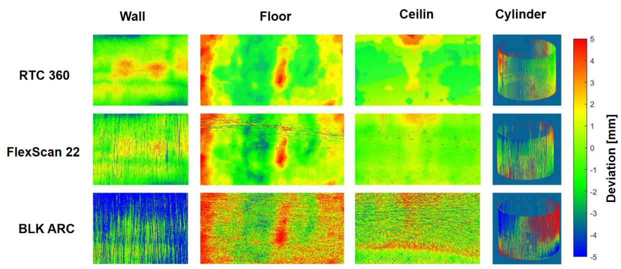


Figure 10. Noise analysis results.

| | RTC360 | Z+F FlexScan 22 | Leica BLK ARC |
|---|---|---|---|
| Test object | STD(mm) | | |
| Wall | 1.2 | 1.4 | 4.6 |
| Ceiling | 0.7 | 1.0 | 2.1 |
| Floor | 1.8 | 2.0 | 3.4 |
| Cylinder | 1.8 | 3.5 | 10.2 |

Table 2. STD results.

## 4.3 Fusion Results

After a comprehensive uncertainty evaluation, Z+F FlexScan 22 was deemed superior, providing a solid foundation for data fusion during simultaneous scanning. Since both systems scanned simultaneously, minimizing inconsistencies in trajectory estimation was essential. Based on previous results, it's clear that Z+F FlexScan 22 significantly outperforms Leica BLK ARC in trajectory estimation. Therefore, in the subsequent trajectory-based fusion, data from Z+F FlexScan 22 is treated as the outperformed point cloud.

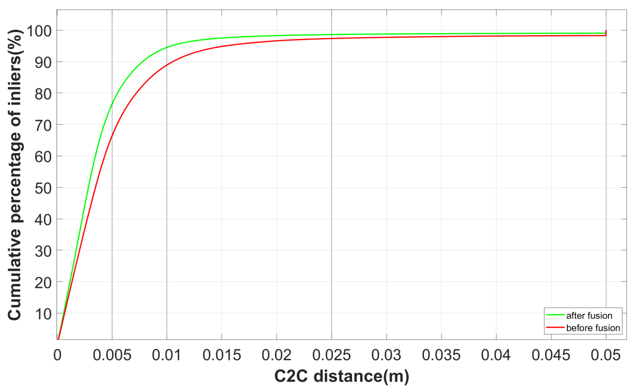


Figure 11. C2C results before and after fusion.

Additionally, the fused point cloud offers improved coverage compared to using a single system, thanks to an inclusion of Leica BLK ARC. However, this also introduces additional noise, making a Moving Least Squares-based denoising step necessary. After completing these fusion steps, we compared the fused point cloud with TLS point cloud using C2C distance. Figure 11 illustrates changes in C2C distances before and after fusion. Figure 12 shows noise analysis results for a selected wall with height and width of 1.5 m and 0.6 m. In both figures, a clear quality improvement is noticeable.

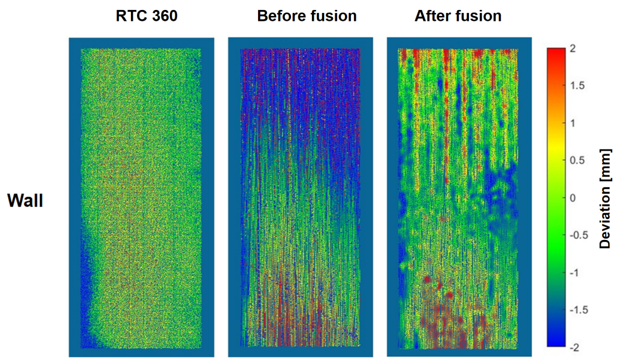


Figure 12. Noise analysis results before and after fusion.

Overall, our proposed uncertainty-aware evaluation and fusion solution delivers positive output and gives a practical way for exploring simultaneous scanning of dual MLS systems.

## 5. Discussion

### 5.1 Potential Reasons for Differentiated Performance of Two Systems

In this paper, despite our extensive efforts in evaluating and quantifying uncertainty, we hypothesize that two main factors contribute to the differences in trajectory estimation and random noise between the two systems. First, Z+F FlexScan 22 uses a high-precision Imager 5016 TLS scanner for data acquisition, giving it an advantage over Leica BLK ARC, which is constrained by its size and cannot accommodate a high-precision LiDAR input. Second, the SLAM algorithms used by two systems differ significantly in our test environment. Overall, identifying error sources in MLS systems remains an open challenge that requires further investigation.

### 5.2 Perspectives of Dual-MLS Simultaneous Scanning Applications

In general, users like to choose an MLS system based on their specific needs, considering factors such as accuracy, cost, size, and environment. For complex indoor scenes, a single system may struggle to capture satisfactory data due to its size or performance limitations. If the dual-system scanning solution described in this paper is feasible, a large, high-precision system can ensure data quality in spacious areas, while a smaller, more flexible system can be used for handheld or backpack scanning in other hard-to-reach areas. By fusing data from both systems, final point cloud could have a chance to achieve greater coverage with high quality.

## 6. Conclusion

In conclusion, this paper explores a potential of a specially designed trolley-based dual MLS platform, enabling simultaneous scanning and uncertainty evaluation of different MLS systems. Our proposed comprehensive uncertainty evaluation workflow offers an in-depth analysis of two state-of-the-art MLS systems, contributing to a better understanding of their respective strengths and weaknesses in practical applications. Additionally, an uncertainty-aware fusion approach, incorporating drift reduction and denoising, demonstrates promise in improving completeness and quality of the fused point cloud. This also provides strong evidence for our hypothesis that a simultaneous scanning of two MLS systems could produce point clouds that are more complete and of higher quality than those generated by a single system.

While these findings suggest potential improvements in MLS system integration, further research is needed to refine the fusion process and assess its applicability in more complex environments. Continued exploration in this area may help optimize a balance between system accuracy and efficiency in diverse data collection scenarios.

## 7. Acknowledgement

This research was funded by TUM Georg Nemetschek Institute of Artificial Intelligence for the Built World, project "NERF2BIM", PI Christoph Holst

## References

Al-Durgham, K., Lichti, D. D., Kwak, E., Dixon, R., 2021. Automated accuracy assessment of a mobile mapping system with lightweight laser scanning and MEMS sensors. *Applied Sciences*, 11(3), 1007.

Alexa, M., Behr, J., Cohen-Or, D., Fleishman, S., Levin, D., Silva, C. T., 2003. Computing and rendering point set surfaces. *IEEE Transactions on visualization and computer graphics*, 9(1), 3–15.

Askar, C., Scheider, A., Sternberg, H. et al., 2023. Evaluation of a State-of-the-Art Indoor Mobile Mapping System in a Complex Indoor Environment. *ZfV-Zeitschrift für Geodäsie, Geoinformation und Landmanagement*.

Barber, D., Mills, J., Smith-Voysey, S., 2008. Geometric validation of a ground-based mobile laser scanning system. *ISPRS journal of photogrammetry and remote sensing*, 63(1), 128–141.

Goel, S., Lohani, B., 2015. Relative contribution and effect of various error sources on the performance of mobile mapping system (MMS). *Journal of the Indian Society of Remote Sensing*, 43, 639–645.

Holst, C., Kuhlmann, H., 2016. Challenges and present fields of action at laser scanner based deformation analyses. *Journal of applied geodesy*, 10(1), 17–25.

Holst, C., Medic, T., Nothnagel, A., Kuhlmann, H., 2019. Analyzing shape deformation and rigid body movement of structures using commonly misaligned terrestrial laser scanners: The radio telescope case. *Proceedings of the 4th Joint International Symposium on Deformation Monitoring (JISDM), Athens, Greece*, 15–17.

Kaiser, T., Clemen, C., Maas, H.-G., 2022. Automatic coregistration of photogrammetric point clouds with digital building models. *Automation in construction*, 134, 104098.

Kerekes, G., Schwieger, V., 2020. Determining variance-covariance matrices for terrestrial laser scans: a case study of the arch dam kops. *Contributions to International Conferences on Engineering Surveying: 8th INGEO International Conference on Engineering Surveying and 4th SIG Symposium on Engineering Geodesy*, Springer, 57–68.

Lehtola, V. V., Kaartinen, H., Nüchter, A., Kaijaluoto, R., Kukko, A., Litkey, P., Honkavaara, E., Rosnell, T., Vaaja, M. T., Virtanen, J.-P. et al., 2017. Comparison of the selected state-of-the-art 3D indoor scanning and point cloud generation methods. *Remote sensing*, 9(8), 796.

Maboudi, M., Bánhidi, D., Gerke, M., 2018. Investigation of geometric performance of an indoor mobile mapping system. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 42, 637–642.

Merkle, D., Reiterer, A., 2023. Automated Method for SLAM Evaluation in GNSS-Denied Areas. *Remote Sensing*, 15(21), 5141.

Nocerino, E., Menna, F., Remondino, F., Toschi, I., Rodríguez-Gonzálvez, P., 2017. Investigation of indoor and outdoor performance of two portable mobile mapping systems. *Videometrics, Range Imaging, and Applications XIV*, 10332, SPIE, 125–139.

Schmitz, B., Kuhlmann, H., Holst, C., 2021. Towards the empirical determination of correlations in terrestrial laser scanner range observations and the comparison of the correlation structure of different scanners. *ISPRS Journal of Photogrammetry and Remote Sensing*, 182, 228–241.

Shan, J., Toth, C. K., 2018. *Topographic laser ranging and scanning: principles and processing*. CRC press.

Shi, B., Bai, Y., Zhang, S., Zhong, R., Yang, F., Song, S., Li, G., 2021. Reference-plane-based approach for accuracy assessment of mobile mapping point clouds. *Measurement*, 171, 108759.

Stenz, U., Hartmann, J., Paffenholz, J.-A., Neumann, I., 2020. High-precision 3D object capturing with static and kinematic terrestrial laser scanning in industrial applications—approaches of quality assessment. *Remote Sensing*, 12(2), 290.

Thomson, C., Apostolopoulos, G., Backes, D., Boehm, J., 2013. Mobile laser scanning for indoor modelling. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 2, 289–293.

Tsakiri, M., Anagnostopoulos, V., 2015. Change detection in terrestrial laser scanner data via point cloud correspondence. *Int. J. Eng. Innov. Res*, 4, 2277–5668.

Tucci, G., Visintini, D., Bonora, V., Parisi, E. I., 2018. Examination of indoor mobile mapping systems in a diversified internal/external test field. *Applied Sciences*, 8(3), 401.

Wujanz, D., Burger, M., Mettenleiter, M., Neitzel, F., 2017. An intensity-based stochastic model for terrestrial laser scanners. *ISPRS Journal of Photogrammetry and Remote Sensing*, 125, 146–155.


https://doi.org/10.5194/isprs-archives-XLVIII-G-2025-1603-2025  