Beyond Accuracy: A Computational–Robustness Comparison of Point Cloud Registration Algorithms

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Keywords: Point Cloud Registration, Cultural Heritage, LiDAR, Photogrammetry, Digital Twins.

Abstract

The digital documentation of cultural heritage increasingly relies on the fusion of multi-source data to overcome the limitations of individual sensors. This study evaluates the performance of four registration algorithms, Iterative Closest Point (ICP), RANSAC, Fast Global Registration (FGR), and FilterReg, applied to the fusion of Terrestrial Laser Scanning (TLS) and UAV-based Structure-from-Motion (SfM) point clouds of the Engenho Central do Bracuhy ruins in Brazil. Given the challenging nature of the dataset, characterized by non-uniform density and inherent SfM noise, we utilized the Multimetric Computational-Prediction Efficiency Index (MCPEI) to jointly assess accuracy and processing time. Results indicate that probabilistic methods, specifically FilterReg, outperform geometric-based approaches in multimodal scenarios. FilterReg demonstrated superior performance to Gaussian noise and outliers, maintaining high efficiency scores (> 0.85) where FGR failed to converge. Furthermore, it exhibited rotation invariance without requiring coarse initialization. These findings suggest that probabilistic filtering is a more suitable paradigm for the automated documentation of complex heritage sites than traditional deterministic optimization.

1. Introduction

Throughout human history, the transition from nomadism to settled societies catalyzed the emergence of complex urban systems (Greenfield, 2016), driving the development of novel architectural structures and technologies. Each city evolved uniquely, resulting in a highly heterogeneous global urban landscape. The conservation of these historical structures serves as a record of past societal dynamics and preserves collective cultural memory. Numerous cities worldwide, such as Rome in Italy, Teotihuacán in Mexico, and Ouro Preto in Brazil, stand as prime examples of historical centers that bridge the past with the present.

Preserving these structures requires proactive governmental intervention, as historical buildings are inherently susceptible to degradation from natural forces and the passage of time. Consequently, effective restoration and reconstruction projects rely on meticulous documentation of the buildings' geometry and structural characteristics (Stylianidis et al., 2022). The Venice Charter (UNESCO, 1972) established an international framework for the conservation and restoration of historical buildings, representing a breakthrough in this field and providing guidelines that remain standard practice today.

The documentation of cultural heritage has evolved towards the creation of "Digital Twins" for comprehensive analysis, a concept consolidated as Digital Heritage (Remondino, 2011; Grussenmeyer et al., 2008). In this context, digital twins can be integrated into broader informational frameworks, establishing the foundation for Historic Building Information Modeling (HBIM). Furthermore, this integration plays a crucial role in the development of smart cities by enabling the generation of advanced spatial products, such as high-resolution maps (Cortés Meseguer and García Valldecabres, 2023). To achieve these high-fidelity models, the integration of Terrestrial Laser Scanning (TLS) with Structure-from-Motion (SfM) photogrammetry has become a standard approach. Similar to its applications in civil infrastructure assessment (Rocha et al., 2025), this multi-sensor fusion provides a comprehensive dataset that individual sensors cannot achieve alone (da Silva Ruiz et al., 2023; Abdelazeem et al., 2021).

While TLS provides geometric precision, it is limited by ground-level occlusions; conversely, UAV-based SfM offers comprehensive coverage but is susceptible to noise and scale inconsistencies (Bolkas et al., 2023). A critical step in fusing these multi-source datasets is point cloud registration (Xu et al., 2023). Traditional rigid registration methods, such as the Iterative Closest Point (ICP) proposed by Besl and McKay (1992), rely on precise initialization and are sensitive to outliers. Robust alternatives like RANSAC (Random Sample Consensus) (Fischler and Bolles, 1987) mitigate these issues but incur high computational costs. More recently, probabilistic methods like FilterReg (Gao and Tedrake, 2019) and global optimization techniques like Fast Global Registration (FGR) (Zhou et al., 2016) have been proposed to address these limitations.

This study evaluates these registration paradigms applied to the *Engenho Central do Bracuhy* ruins. We propose a comparative analysis using the Multimetric Computational-Prediction Efficiency Index (MCPEI), adapted from Maia et al. (2025), to determine which algorithm best balances accuracy and processing time for heritage documentation.

2. Material and Methods

2.1 Study Area

The study area comprises the ruins of the Bracuhy Central Sugar Mill (*Engenho Central do Bracuhy*), located in Angra dos Reis, Brazil. Established in 1881 as an innovative industrial complex for sugar production, the site gained international recognition before ceasing operations in the late 19th century due to economic shifts and the abolition of slavery (Machado, 1995). Despite inclusion in tourism development plans during the 1970s, specifically the Porto do Bracuhy project, the site has faced long-standing challenges regarding heritage preservation and structural integrity (Vieira de Carvalho, 2009). The Study Area location is depicted in Fig. 1

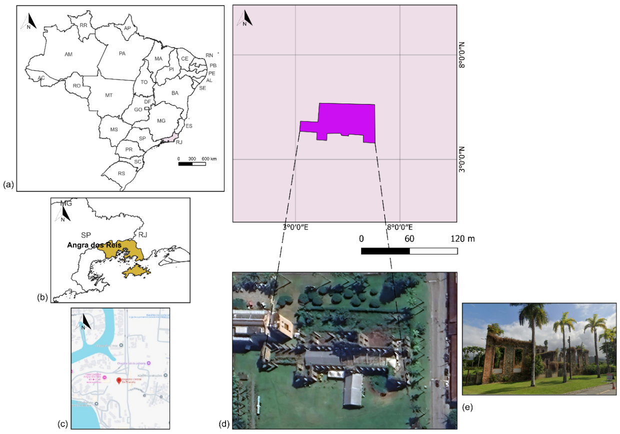


Figure 1. Study Area.

Currently, the remaining structures present a complex geometric environment characterized by weathering and structural decay. This scenario poses significant challenges for point cloud acquisition and registration, making it an ideal testbed for evaluating the proposed accuracy and processing time metrics.

2.2 Scenarios

To evaluate the effectiveness and robustness of the proposed registration algorithms, a controlled set of simulated experiments was developed. Distinct test scenarios were generated based on two main types of perturbations: spatial displacements and the insertion of synthetic noise. Initially, a ground truth was established via manual alignment followed by the Iterative Closest Point (ICP) algorithm between the original terrestrial LiDAR cloud and the reference photogrammetric point cloud. From this registered LiDAR dataset, known spatial transformations and noise models were applied to generate the test scenarios, ensuring that the optimal transformation matrix required to recover the original position was mathematically defined.

To simulate various initialization conditions typically encountered in field surveys, three levels of angular displacement around the vertical axis (Z-axis) were introduced. The lowest level (10°) simulates a minor alignment error where the point clouds are in close proximity. The intermediate level (20°) represents a moderate challenge designed to test the convergence limits of local algorithms. Lastly, the severe level (40°) establishes a stress scenario, simulating the absence of reliable initial orientation data. A small translational displacement was also applied alongside the rotations. The exact parameters for rotation and translation applied in each scenario are detailed in Table 1.

In addition to spatial displacements, synthetic noise was introduced to evaluate the algorithms' resilience to sensor limitations and environmental artifacts. Two specific noise models were applied:

Outlier Noise: Outliers represent spurious data that do not correspond to the physical surface of the object of interest. According to Pomerleau et al. (2015), these anomalies can originate from dynamic objects moving through the scene, such as pedestrians or birds, or, as highlighted by Charron et al. (2018), from adverse environmental conditions (e.g., suspended dust, rain) that generate false sensor returns. To simulate this condition and test the filtering capabilities of the algorithms, 115,000 points were randomly inserted into the scene volume, corresponding to approximately 0.5% of the original point cloud (which contains roughly 23 million points).

Gaussian Noise: Gaussian noise simulates the inherent measurement uncertainty of scanning sensors. According to Thrun et al. (2006), the distance error in laser rangefinders is modeled by a normal distribution. In TLS surveys, this manifests as a dispersion of points around the true surface, caused by the instrument's precision limitations, material reflectance properties, and the beam's angle of incidence (Soudarissanane et al., 2011). In this study, normally distributed noise was applied to a sample set corresponding to 0.1% of the point cloud points, aiming to evaluate the algorithms' sensitivity to different noise conditions.

Scenario	Rotation in X (°)	Rotation in Y (°)	Rotation in Z (°)	Z Displacement (m)	Total Displacement (m)
10°	1.00	1.00	10.00	-2.00	2.00
20°	2.00	2.00	20.00	-4.00	4.00
40°	4.00	4.00	40.00	-8.00	8.00

Table 1. Parameters applied for the generation of test scenarios.

2.3 Evaluated Registration Algorithms

Four algorithms representing different registration strategies were selected:

2.3.1 Iterative Closest Point (ICP) The standard for fine registration, ICP minimizes the Euclidean distance between nearest neighbors (Besl and McKay, 1992). It is a local optimization method, requiring good initial alignment to avoid local minima, particularly in datasets with partial overlap (Rusinkiewicz and Levoy, 2001).

2.3.2 RANSAC A robust feature-based estimator that employs a "hypothesize-and-verify" strategy to handle outliers (Fischler and Bolles, 1987). While effective in noisy environments, its non-deterministic nature can lead to excessive runtime in dense point clouds.

2.3.3 Fast Global Registration (FGR) Proposed by Zhou et al. (2016), FGR is a deterministic global approach that optimizes a line process objective function. It is designed to operate without initialization but can be sensitive to the high-frequency noise typical of SfM-derived data.

2.3.4 FilterReg A probabilistic method proposed by Gao and Tedrake (2019) that treats registration as a maximum likelihood estimation problem using a Gaussian filter. It offers robustness to noise and outliers comparable to heavier probabilistic methods but with computational efficiency similar to ICP.

2.4 Calculation of Computational-Efficiency Index

To assess the computational efficiency of the evaluated algorithms while integrating performance metrics of different natures, the Multimetric Computational–Prediction Efficiency Index (MCPEI) was employed. The MCPEI was originally proposed as an evaluation metric for decision-tree-based machine learning algorithms. In this study, the index was adapted to incorporate processing time as a measure of computational cost and RMSE and fitness score as indicators of predictive quality.

Since the evaluated metrics present different numerical scales, a min–max normalization was applied to map all values into the [0 , 1] [0,1] interval.

For minimization metrics, in which lower values indicate better performance (e.g., processing time and RMSE), the normalized score S_{min} is defined as:

$$S_{\text{min}}(x) = \frac{\max(X) - x}{\max(X) - \min(X)} \tag{1}$$

Conversely, for maximization metrics, in which higher values represent better performance (e.g., fitness), the normalized score S_{max} is given by:

$$S_{\text{max}}(x) = \frac{x - \min(X)}{\max(X) - \min(X)} \tag{2}$$

where X denotes the set of observed values for a given metric across all evaluated algorithms.

The MCPEI is computed as a weighted mean combining computational cost and prediction quality. The computational cost score (C_{score}) and the metric quality score (M_{score}) are defined as:

$$C_{\text{score}} = S_{\text{time}},\ M_{\text{score}} = \frac{S_{\text{RMSE}} + S_{\text{fitness}}}{2}. \tag{3}$$

The final MCPEI value is calculated as:

$$\text{MCPEI} = \frac{1}{2}\left(\frac{1}{|M|}\sum_{m\in M} m \ + \ \frac{1}{|C|}\sum_{c\in C} c\right), \tag{4}$$

where $M = \{\text{RMSE}, \text{Fitness}\}$ and $C = \{\text{processing time}\}$ denotes the set of normalized computational cost metrics.

Finally, to assess whether statistically significant differences exist among the medians of the algorithmic groups, the Kruskal–Wallis H test was applied. Upon detection of a significant global difference, pairwise comparisons were conducted using the Mann–Whitney U test to identify statistically significant superiority between specific pairs of algorithms.

2.5 Data Acquisition

The point cloud dataset represents the ruins of the Bracuhy Central Sugar Mill (Engenho Central do Bracuhy). The reference point cloud was generated via Structure-from-Motion (SfM) using images captured by a DJI Mavic 3M Unmanned Aerial Vehicle (UAV) (Fig. 2a). To ensure comprehensive and high-resolution coverage, both orthogonal (25 m altitude) and oblique (45°) flight paths were executed, acquiring a total of 1,235 images with 80% frontal and 75% lateral overlap. The resulting Ground Sample Distances (GSD) were 1.16 cm/px for the orthogonal flight and 1.68 cm/px for the oblique flights. The SfM processing was conducted using Agisoft Metashape Professional. This dataset was selected as the reference due to its precise georeferencing acquired via the UAV's onboard Real-Time Kinematic (RTK) positioning module.

The source point cloud was acquired using a Faro Focus Premium 70m terrestrial LiDAR scanner, providing high geometric fidelity (Fig. 2b). To mitigate occlusions caused by terrain irregularities and surrounding vegetation, the multi-scan method was applied, collecting data from 41 different scan positions around the target. Standard highly reflective spherical targets were distributed throughout the scene to assist in the initial coarse registration of the individual scans.

Both datasets underwent preprocessing using CloudCompare. After spatially cropping the clouds to isolate the region of interest, the LiDAR data, which originally possessed a significantly higher point density, was subjected to random subsampling. This process retained approximately 2.3% of the original TLS data, reducing it to a total of 22,215,411 points. This standardization aligns the LiDAR density with the photogrammetric cloud, preventing computational bias toward the denser dataset during the evaluation of the registration algorithms.

All experiments were performed on a computing environment equipped with an AMD EPYC 7763 64-Core Processor and 1 TB of RAM. The system also features an NVIDIA A100-SXM4 GPU (80 GB VRAM). To ensure a consistent baseline for the computational cost assessment (MCPEI), the processing time for all registration algorithms was measured using a single-core configuration, avoiding variations due to multi-threading efficiency.

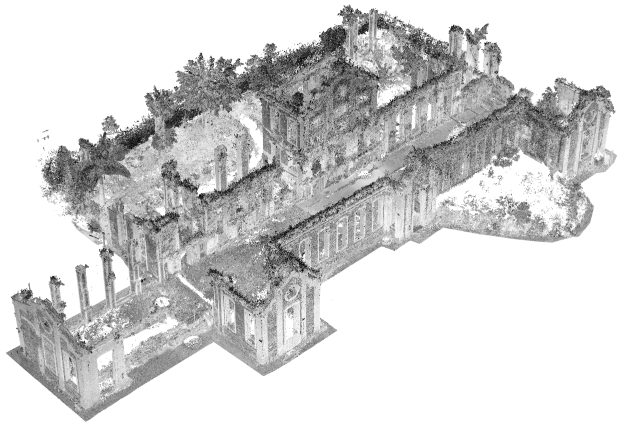
3. Results

The quantitative evaluation was conducted using the Multimetric Computational-Prediction Efficiency Index (MCPEI), which aggregates accuracy metrics (RMSE, Fitness) and computational cost (Processing Time) into a single normalized score ranging from 0 to 1. The following subsections detail the comparative performance across different registration scenarios.

3.1 Overall Performance Assessment

In the baseline scenario (noise-free and pre-aligned), the *FilterReg* algorithm achieved the highest efficiency score (0.901), demonstrating a superior balance between solution quality and runtime. As shown in Fig. 3, this probabilistic approach significantly outperformed the feature-based method FGR, which recorded the lowest MCPEI (0.303). The standard ICP and RANSAC methods showed intermediate performance, with indices of 0.679 and 0.507, respectively. These results suggest that for the specific density and topology of the Bracuhy ruins dataset, probabilistic filtering offers the best trade-off between convergence speed and geometric precision.

(a) Photogrammetry



(b) LiDAR

Figure 2. Visual comparison of the datasets. (a) The photogrammetric point cloud with RGB color and (b) the terrestrial LiDAR point cloud.

3.2 Robustness to Noise and Outliers

Given that the source point cloud was generated via SfM (drone photogrammetry), susceptibility to noise is a critical evaluation parameter. Fig. 4 presents the MCPEI variation under Gaussian noise (0.1%) and outlier contamination (0.5%). In the Gaussian noise scenario, *FilterReg* demonstrated remarkable stability, maintaining high efficiency values (> 0.7). Conversely, FGR's performance collapsed (MCPEI < 0.15), indicating high sensitivity to local surface variations typical of SfM data. Regarding outliers, while their introduction reduced the global scores for all algorithms due to increased processing time and RMSE penalties, *FilterReg* remained the top-performing algorithm. It proved to be robust against artifacts, whereas geometric-only approaches struggled to filter non-overlapping correspondences effectively.

3.3 Rotation Invariance Analysis

To assess the convergence basin without manual coarse alignment, rotational offsets of $10°$, $20°$, and $40°$ were applied to the source cloud. As depicted in Fig. 5, *FilterReg* exhibited rotation invariance, with its MCPEI remaining consistently high (≈ 0.9) regardless of the initialization angle. In contrast, the standard ICP performance degraded linearly as the rotation increased, dropping below 0.6 at $20°$ and failing to converge satisfactorily at $40°$. This confirms that the probabilistic framework of FilterReg is less dependent on initial alignment compared to traditional iterative methods, making it more suitable for automated workflows in complex heritage sites.

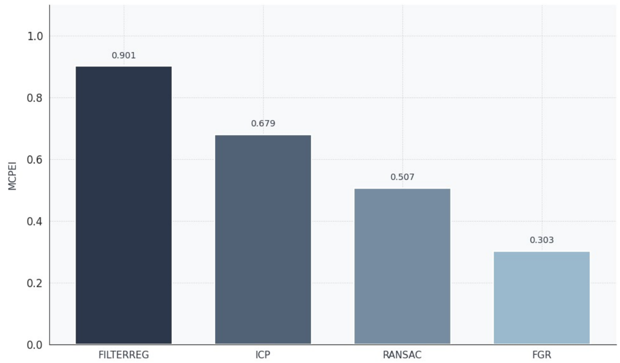


Figure 3. Overall performance comparison using MCPEI index.

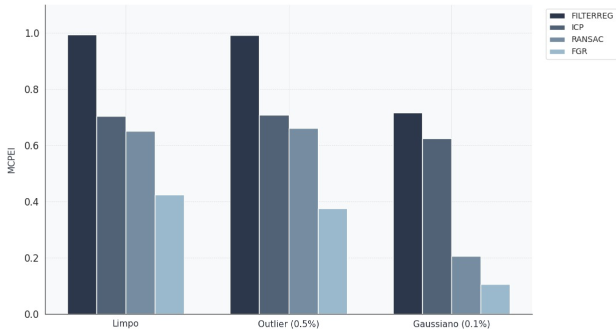


Figure 4. Assessment of algorithm robustness to data imperfections.

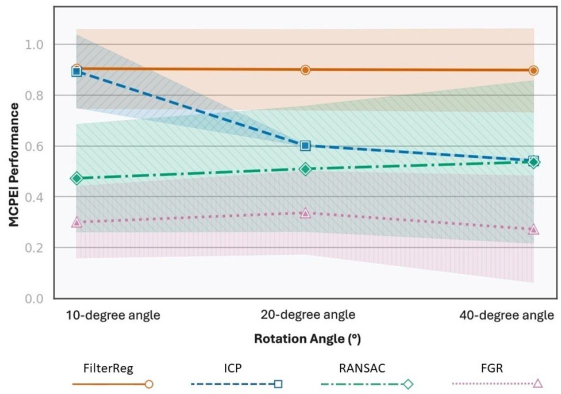


Figure 5. Rotation invariance analysis evaluating the convergence basin of the algorithms.

4. Conclusion

This work investigated the efficiency of rigid registration algorithms for fusing TLS and SfM datasets in a complex historical environment. By adopting the MCPEI metric, we moved beyond simple accuracy assessment to evaluate the critical trade-off between geometric fidelity and computational cost.

The inherent noise in SfM-derived point clouds significantly impacts deterministic global algorithms. While FGR offers computational speed, its performance degrades drastically under Gaussian noise, making it unsuitable for raw photogrammetric data without pre-filtering. Similarly, traditional ICP remains the standard for fine precision but lacks the robust convergence basin required for automated workflows, failing to register clouds with rotational offsets greater than 20° in our tests.

The FilterReg algorithm emerged as the most balanced and resilient solution. Its probabilistic characteristic effectively filtered outliers and handled the variations between the terrestrial LiDAR and UAV-based data, achieving the highest MCPEI scores across all scenarios.

Beyond the algorithmic evaluation, these findings have direct implications for the preservation of cultural heritage. The reliable and automated fusion of multi-sensor data is a bottleneck in the generation of high-fidelity Digital Twins. By demonstrating that probabilistic methods like FilterReg can operate effectively under stress conditions, without the need for precise manual initialization or extensive noise removal, this study provides a geometric foundation for Historic Building Information Modeling (HBIM). Consequently, it streamlines the transition from raw point clouds to actionable 3D repositories, supporting smarter conservation strategies and the integration of historical sites into the broader context of smart cities.

Future research will focus on extending this comparative framework to include deep learning-based registration paradigms and evaluating their performance and generalization capabilities across diverse architectural typologies.

5. Acknowledgments

The authors acknowledge the financial support from the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior(CAPES), Brazil (Finance Code 001); FAPESP(Grant 2020/09215-3); CNPq (Grant 311324/2021-5); SAC(Grant 00413/2025); the Postgraduate Program in Aeronautical Infrastructure Engineering at Aeronautics Institute of Technology (ITA) and the Postgraduate Program in Remote Sensing(PGSER) at the National Institute for Space Research (INPE)

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