# Semantically-Driven Adaptive Registration for Correcting Non-Constant Drift in Multi-Temporal MLS Data

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**ABSTRACT:**

Mobile Laser Scanning (MLS) provides high-accuracy 3D point clouds essential for road infrastructure monitoring. However, multi-temporal MLS analysis is often limited by non-constant, spatially varying trajectory drift caused by GNSS outages and IMU inaccuracies. These misalignments can exceed the magnitude of the changes being monitored, such as pavement deformation, making accurate change detection challenging. This paper presents a fully automatic, semantically driven registration pipeline designed to correct spatially varying drift in directly georeferenced MLS data. The method first applies Principal Component Analysis (PCA) and intensity-based filtering to classify points into stable geometric categories, including flat horizontal surfaces, flat vertical structures, and linear vertical features. A correspondence-based filtering step removes dynamic objects and temporal changes to ensure that registration is driven by stable geometry. The core of the method is an adaptive piecewise registration strategy, where the reference point cloud is divided into sequential 1-meter patches. Each patch is assigned a local rigid transformation estimated using an adaptively expanding registration window guided by the availability of stable vertical features. A final smoothing step ensures spatial continuity between adjacent transformations. The method was evaluated on two MLS datasets collected one year apart along a 3 km road corridor using the FGI Roamer-R4DW system. Validation using 30 independent ground signals showed that the 3D RMSE improved from 3.38 cm to 1.54 cm, with vertical RMSE improving from 2.54 cm to 0.67 cm. The results demonstrate that the proposed approach enables centimeter-level alignment suitable for high-precision multi-temporal road monitoring and change detection applications.

## 1. Introduction

Mobile Laser Scanning (MLS) systems, such as the FGI Roamer-R4DW, provide dense, high-accuracy 3D point clouds essential for road infrastructure management (El Issaoui et al., 2026, 2021). The ability to capture multi-temporal datasets, often separated by several years, presents a significant opportunity for automated change detection, asset monitoring, and HD map updating (Gehrung et al., 2020; Vosselman et al., 2004).

However, a critical and persistent challenge in multi-temporal MLS analysis is data alignment. While modern MLS systems are directly georeferenced using tightly coupled GNSS-IMU trajectories, they still suffer from non-constant, non-rigid drift (Wang et al., 2026). This drift accumulates from trajectory inaccuracies, particularly from GNSS outages in urban canyons or forested areas, resulting in small, spatially varying misalignments in all dimensions ($x$, $y$, $z$) (Rincon et al., 2025). When comparing multi-temporal datasets, these local deviations, which can be decimeter-level (Yan et al., 2018), are often larger than the changes one wishes to detect (e.g., pavement deformation). Global registration techniques, such as Iterative Closest Point (ICP) and its robust variants (Besl and McKay, 1992), can reduce a constant bias between epochs but are inherently limited to a single rigid transformation, and therefore leave spatially varying drift uncorrected.

Recent work has moved toward more flexible registration strategies. Studies have introduced non-rigid or fragment-wise registration strategies for MLS strip adjustment (Rincon et al., 2025; Yan et al., 2018), while Zhao et al. (2022) proposed a trajectory correction model based on adaptive segmentation, stable geometric features, and global pose optimization for city-scale MLS datasets. Xu et al. (2024) demonstrated that stable pole-like objects can provide robust correspondences for high-accuracy multi-temporal registration in urban environments, and Wang et al. (2026) used road markings as control features for spatial consistency correction in road scenes. Hussnain et al. (2021) showed that MLS trajectory accuracy can also be improved by integrating external high-accuracy aerial imagery in a spline-based adjustment framework. These studies show that high-accuracy multi-temporal registration typically depends on either stable geometric features, external reference data, or both. Existing methods are effective when stable control features, such as poles, road markings, or external reference data, are available. In long road corridors, however, these features are not distributed uniformly, so a registration method must remain robust also in sections where the local geometry is weak or semantically sparse.

To address this gap, we propose a registration pipeline that corrects for non-constant drift using an adaptive, piecewise rigid model. The method calculates a unique 4×4 rigid transformation matrix for each 1-meter patch of the road environment. The novelty lies in its semantically driven, adaptive approach, which ensures that each local transformation is calculated using the most stable features available. In contrast to methods that depend on one feature type only, such as poles or road markings, the proposed pipeline adapts the registration window to the local semantic content, enabling robust correction also in feature-poor road sections.


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## 2. Methodology

### 2.1 Study area and MLS data acquisition

The study area is located in the municipality of Kirkkonummi, Southern Finland (60°09'46"N, 24°32'21"E), where an approximately 3 km long section of a two-lane regional road (road number 11311) was selected as the test site. The road environment represents typical Finnish regional road conditions with varying pavement quality and surrounding infrastructure. The selected section includes straight segments, curved sections with varying curvature, and elevation differences of approximately 14 m, with local slopes exceeding 7%.

The surrounding environment varies significantly along the road corridor. The beginning of the study area passes through a small suburban residential area containing buildings, roadside structures, and other vertical features. Further along the corridor, the environment transitions into predominantly vegetated areas consisting mainly of trees, followed by more open sections including roadside fields with sparse vertical structures. As a result, the dataset contains both feature-rich urban sections and feature-poor rural sections, providing a representative test environment for evaluating registration robustness under varying geometric conditions. Additionally, minor real-world changes between the acquisition epochs, including newly constructed structures, further increase the representativeness of the dataset for multi-temporal analysis.

Two MLS datasets acquired in different years were used in this study. The first dataset was collected in summer 2018 and the second in summer 2019. Surveys were conducted at typical driving speeds of 40-50 km/h under dry weather conditions. Both datasets were acquired using the same MLS platform: the FGI Roamer-R4DW (El Issaoui et al., 2021), hereafter referred to as Roamer. The Roamer system integrates a GNSS-IMU positioning system with multiple laser scanners. The positioning solution is obtained using a NovAtel ISA-100C inertial measurement unit combined with a NovAtel PwrPak7 GNSS receiver to provide direct georeferencing of the point clouds. The system is equipped with two laser scanners, a Riegl VUX-1HA and a Riegl miniVUX-1UAV; however, only the VUX-1HA scanner was used in this study.

The VUX-1HA scanner was mounted approximately 2.9 meters above the road surface with an oblique mounting angle of approximately 15° relative to the vertical axis, allowing acquisition of the surrounding road environment with a 360° field of view. The scanner was operated at 250 scan lines per second with a pulse repetition frequency of approximately 1 MHz, resulting in profile spacings of approximately 4-5 cm and point spacings of approximately 4-6 mm on the road surface at typical driving speeds. The ranging accuracy of the scanner is specified as 5 mm with a precision of approximately 3 mm. Figure 1 shows the Roamer-R4DW system mounted on the measurement vehicle and illustrates the data acquisition geometry and resulting point cloud coverage of the road environment.

### 2.2 Pre-processing and Semantic Classification

Both datasets are directly georeferenced using tightly coupled GNSS-IMU trajectories, providing a common global coordinate frame and an initial alignment sufficient to locate corresponding 1-meter road segments. To improve numerical stability during processing, both point clouds are translated toward the origin using a constant shift vector. The data are then voxel-downsampled to reduce computational cost while preserving the underlying geometry. In this study, a voxel size of 5 cm was used.

Local geometric features are extracted using a neighborhood-based Principal Component Analysis (PCA). For each point, PCA is computed from its 30 nearest neighbors to derive eigenvalue-based geometric descriptors and the local surface normal. From these, the normalized largest eigenvalue,

Figure 1. FGI Roamer-R4DW mobile mapping system used in this study. The figure shows the sensor configuration on the survey vehicle and illustrates the 360° scanning geometry and resulting point cloud coverage of the road environment (adapted from El Issaoui et al., 2026).

normalized smallest eigenvalue, and the angle between the surface normal and the vertical direction (α) are used to characterize the local structure of the point cloud.

These geometric descriptors, together with the laser intensity attribute, are used to filter and classify points into three stable geometric classes: (1) flat horizontal surfaces (primarily road surfaces), (2) flat vertical surfaces (primarily building façades), and (3) linear vertical structures (such as poles, tree trunks, and building edges). The classification is based on thresholding normal orientation, eigenvalue-based geometric properties, and intensity. After classification, class-specific voxel downsampling is applied to balance geometric detail and computational efficiency. In this study, voxel sizes of 0.05 m, 0.1 m, and 0.5 m were used for linear vertical, flat vertical, and flat horizontal classes, respectively. This preserves fine detail in poles, tree trunks, and edges, while reducing redundancy in large planar road surfaces.

To improve registration robustness, the pipeline further removes points unlikely to provide stable correspondences. This denoising step includes removing small, isolated segments, filtering points located far from the road corridor, and removing points that do not have spatial correspondences in the other epoch based on nearest-neighbor searches. This process reduces the influence of dynamic objects and real-world changes such as vegetation growth, new structures, and temporary objects, ensuring that the registration is primarily driven by stable scene geometry.

The resulting filtered point clouds consist mainly of geometrically stable features suitable for the adaptive piecewise registration described in the following section.

### 2.3 Adaptive Patch-Based Registration

The core of the method is a piecewise registration strategy that adapts to the local availability of stable geometric features. The reference point cloud is first divided into sequential 1-meter patches along the MLS trajectory, and each slice is treated as an individual patch with its own index. For each patch, a “feature score” is computed as the proportion of vertical points, defined as points classified as flat vertical or linear vertical features. The score is quantized and used to guide the adaptive selection of registration neighborhoods.

To register a target patch $i$, an adaptive registration window is constructed around the corresponding reference patch. The window is initialized with neighboring patches and expanded symmetrically along the trajectory until two conditions are satisfied: (1) a minimum number of patches is included (21 patches in this study), and (2) the cumulative feature-support score within the window exceeds a predefined threshold. This ensures that sufficient stable geometric features are available for reliable registration.

This strategy allows feature-poor regions, such as open road sections, to be registered using stable features located further along the corridor, such as building façades, tree trunks, or roadside infrastructure, improving robustness in areas where local geometry alone would be insufficient.

Once the adaptive window is defined, a plane-to-plane ICP registration is performed to estimate the 4×4 rigid transformation matrix for patch $i$. The initial transformation is estimated from previously computed neighboring transformations to improve convergence stability. Transformations producing unrealistic rotation changes are rejected to prevent local registration failures. This procedure is repeated sequentially for all n patches along the trajectory.

### 2.4 Transformation Smoothing

The registration process outputs an array of $n$ local rigid transformations corresponding to the individual 1-meter patches. Since these transformations are estimated independently, small discontinuities may occur between adjacent patches. To ensure spatial consistency along the trajectory, a final smoothing step is applied.

For each patch, the final transformation is computed as the average of the transformations of neighboring patches within a ±5 patch window, resulting in an effective window size of 11 patches. The averaging is performed separately for translation and rotation components. The rotation matrices are first converted into roll, pitch, and yaw angles, after which the mean rotation angles and mean translations are computed and used to reconstruct the final rigid transformation.

This smoothing reduces small discontinuities between adjacent patches and results in a spatially continuous correction of the non-constant drift along the entire road section. In practice, the step ensures smooth transitions between neighboring local transformations while preserving the overall registration accuracy.

## 3. Results and discussion

The proposed pipeline was evaluated qualitatively and quantitatively. Figure 2 shows the semantic classification used in the registration, where the retained point classes represent flat horizontal, flat vertical, and linear vertical structures. As discussed in Section 2, the registration is driven by the geometrically stable subset of the scene rather than the full point cloud, which reduces the influence of real temporal changes and unstable objects. The resulting classification is well suited for this road corridor, which contains both feature-rich suburban sections and more weakly constrained rural sections.

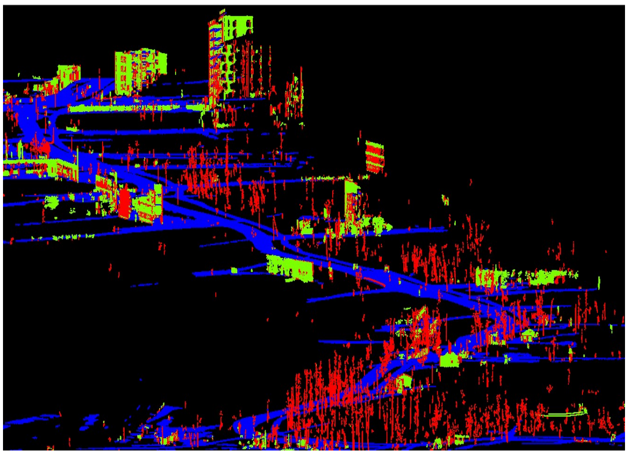

Figure 2. Visualization of semantic classification result. Blue indicates flat horizontal surfaces (road surface), yellow represents flat vertical surfaces (building façades), and red highlights linear vertical features such as trees, poles, and building edges.


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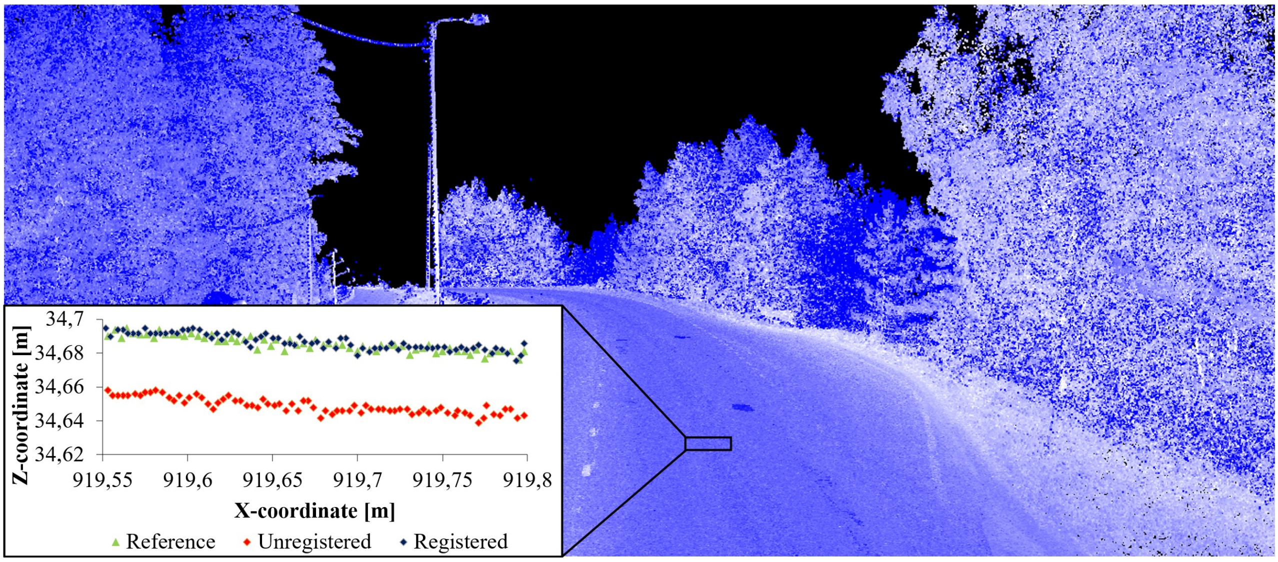


Figure 3. Visualization of registration results. The image shows the reference MLS point cloud (blue) of the road environment. The inset provides a magnified vertical (XZ) cross-section of the road surface, showing the initial unregistered data (red) with significant drift, the reference data (green), and the registered data (dark blue) after applying our algorithm.

Figure 3 illustrates a representative registration result. Before registration, the two epochs show clear local misalignment in both horizontal and vertical directions. In the magnified XZ cross-section, the initial discrepancy is mainly visible in the vertical component, which is the most critical direction for road-surface monitoring. After applying the adaptive piecewise registration, the corrected target data follow the reference road surface closely, and the local drift visible in the initial alignment is largely removed. The visual result is consistent with the objective of the method, namely, to refine the directly georeferenced MLS point clouds to a level suitable for detailed multi-temporal analysis.

For quantitative evaluation, painted hourglass-shaped ground signals introduced in the rutting experiment of El Issaoui et al. (2021) were used as independent validation features. The signals were originally painted at approximately 50-meter intervals along the road corridor, following the spacing of the roadside streetlamps. Due to wear of the markings between epochs, only 30 signals that remained clearly visible in both datasets were used in the analysis. As shown in Figure 4, the signal centers were manually identified from the reference MLS dataset (2018), the initially georeferenced 2019 dataset, and the registered 2019 dataset. The registration error was then calculated from the differences between the corresponding signal centers.

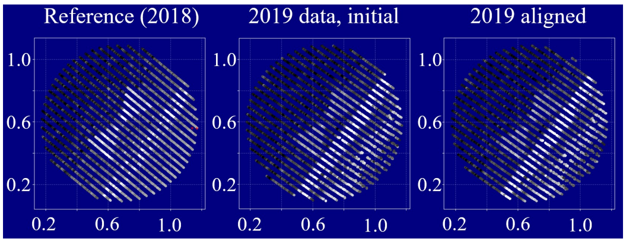


Figure 4. Example of a painted hourglass-shaped ground signal used for registration accuracy evaluation. The figure shows the signal from the reference MLS dataset (2018), the initially georeferenced 2019 dataset, and the 2019 dataset after applying the proposed registration. The signal centers were manually selected and used to quantify the registration error.

Table 1 summarizes the bias, RMSE, and standard deviation before and after registration. The results show a clear improvement in all components. The 3D RMSE decreased from 3.38 cm to 1.54 cm, while the horizontal RMSE decreased from 2.22 cm to 1.38 cm. The largest improvement was observed in the vertical component, where the RMSE decreased from 2.54 cm to 0.67 cm. This is an important result for road applications, since change detection of rutting, pavement deformation, or surface distress is particularly sensitive to vertical misalignment. The corresponding error distributions at the 30 validation signals are shown in Figure 5. The improvement is not limited to a few isolated points, but is visible along the full 3 km road section. In particular, the vertical error is consistently reduced at nearly all validation locations.

| Metric | Before | After |
|---|---|---|
| XYZ bias (cm) | 3.24 | 1.41 |
| XYZ RMSE (cm) | 3.38 | 1.54 |
| XYZ std. dev. (cm) | 0.97 | 0.62 |
| XY bias (cm) | 2.01 | 1.25 |
| XY RMSE (cm) | 2.22 | 1.38 |
| XY std. dev. (cm) | 0.96 | 0.60 |
| Z bias (cm) | 2.26 | 0.50 |
| Z RMSE (cm) | 2.54 | 0.67 |
| Z std. dev. (cm) | 1.15 | 0.45 |

Table 1. Registration accuracy statistics at 30 validation signals distributed along the study corridor before and after applying the proposed registration. Reported metrics include bias, RMSE, and standard deviation for the 3D (XYZ), horizontal (XY), and vertical (Z) components.

The component-wise results are also meaningful from an application perspective. The largest improvement was obtained in the vertical direction, where the RMSE decreased from 2.54 cm to 0.67 cm. This is expected since vertical errors are

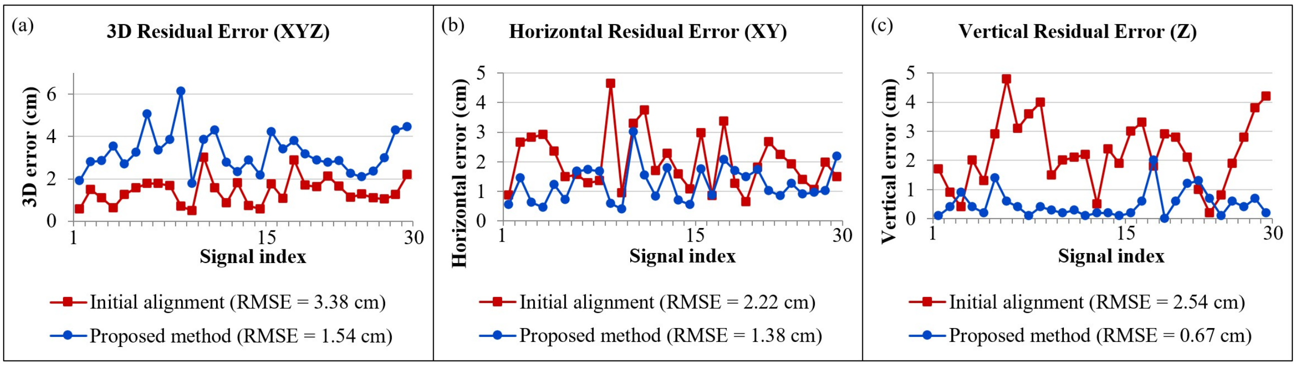


Figure 5. Registration errors at 30 validation signals along the 3-km study road. Errors are shown for the initial georeferencing and after applying the proposed registration method for (a) 3D error (XYZ), (b) horizontal error (XY), and (c) vertical error (Z). The results show consistent improvement across the entire road section, with the largest reduction observed in the vertical component.

typically the dominant component in directly georeferenced MLS data due to GNSS satellite geometry and trajectory drift propagation. This is particularly important for road applications, where pavement distress detection, rut monitoring, and deformation analysis are primarily sensitive to vertical inconsistencies between epochs. The horizontal component also improved from 2.22 cm to 1.38 cm. Although the improvement is more moderate, it still enables more reliable spatial localization of detected defects and improves the consistency of multi-temporal object-level comparisons.

The achieved accuracy indicates that the proposed method is suitable for high-precision multi-temporal road monitoring. For local surface damage, such as cracks and small distress areas, the achieved registration accuracy is likely sufficient to support reliable change detection. However, for broader and smoother roadway deformations, such as rutting or gradual surface settlement, part of the physical change may in principle be partially absorbed by the registration process since road surface points also contribute to the local transformation estimation. This effect is most relevant when the deformation extends continuously over a significant portion of the registration window.

A possible direction for future work is therefore to investigate registration strategies that rely more strongly on stable roadside features and less on the traffic-bearing carriageway. For example, registration could be constrained primarily using façades, poles, sidewalks, and roadside terrain while reducing the influence of the driving lane itself. This could help preserve genuine road-surface deformation signals in cases where the objective is not only geometric alignment but also accurate deformation quantification at the corridor level.

The validation arrangement should also be interpreted critically. Since the painted hourglass signals were placed near streetlamps, the vicinity of the validation points typically contains vertical structures that support the registration. In this sense, the reported results may be slightly optimistic compared to completely feature-poor environments. On the other hand, the adaptive registration window always includes at least 21 m of the corridor length, which in this study provides a high probability of incorporating additional stable roadside objects even when the immediate surroundings of a patch are weakly constrained. The results can therefore be considered representative for this type of regional road environment, although further evaluation would be beneficial in corridors with very limited man-made structures, such as forest roads.

A further direction would be to evaluate the approach against an independent external reference, such as airborne laser scanning (ALS) data or other national reference datasets, similarly to the map-supported strategy proposed by Vezeteu et al. (2026). Many countries already provide nationwide ALS datasets, and although these point clouds are typically sparser than MLS data, their density is continuously improving. Such datasets could provide an additional common reference frame for evaluating multi-epoch consistency, particularly for long-term infrastructure monitoring applications.

Despite these limitations, the presented results show that the proposed semantically driven adaptive registration provides a robust refinement of directly georeferenced multi-temporal MLS data. The achieved centimeter-level consistency, particularly in the vertical component, is sufficient for high-precision road monitoring and supports practical multi-temporal change detection in real road environments.

## 4. Conclusion

This paper presented a semantically driven adaptive registration pipeline for correcting non-constant drift in multi-temporal MLS point clouds. The proposed method combines semantic classification, adaptive piecewise rigid registration, and transformation smoothing to refine directly georeferenced MLS datasets without requiring external control targets or dense artificial reference features. By adapting the registration window based on the availability of stable geometric features, the method remains robust in both feature-rich and feature-poor sections of long road corridors.

The results demonstrate that the proposed approach significantly improves the alignment between multi-temporal MLS datasets. The overall 3D RMSE was reduced from 3.38 cm to 1.54 cm. The most significant improvement was observed in the vertical component, where the RMSE decreased from 2.54 cm to 0.67 cm, while horizontal errors were also successfully reduced from 2.22 cm to 1.38 cm. This level of accuracy is sufficient for detailed multi-temporal road monitoring tasks, particularly those requiring reliable vertical consistency such as pavement distress detection, deformation monitoring, and change detection of road surface condition.

The results further demonstrate that semantically guided feature selection improves registration robustness by ensuring that the alignment is driven primarily by geometrically stable structures rather than by temporal changes or dynamic objects. By restricting the registration to stable scene elements, the method reduces the influence of features that change between epochs and improves the reliability of the local transformations.

At the same time, the results indicate that the method should be applied with consideration when the objective is deformation quantification rather than purely geometric alignment. Since road surface points contribute to the local rigid transformation estimation, broad and spatially smooth physical changes such as rutting or gradual settlement may be partially absorbed by the registration process. This effect is less critical for localized defects such as cracks or potholes but should be considered when analyzing large-scale surface deformation.

Overall, the proposed method provides a practical and scalable approach for refining directly georeferenced MLS datasets for multi-temporal infrastructure monitoring. The results demonstrate that semantically driven adaptive registration can achieve centimeter-level consistency without requiring additional field control, supporting the growing need for reliable long-term road asset monitoring from MLS data.

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