Modeling the Distribution of TLS Distance-Related Uncertainties for Calibration of Geodetic Sensors

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Key words: Engineering survey; Terrestrial Laser Scanning; Calibration of Geodetic Sensors; Uncertainty Modeling; Machine Learning; Probabilistic Regression

SUMMARY

Accurate calibration of terrestrial laser scanners (TLSs) is essential for high-precision applications like deformation monitoring and structural health assessment. TLS-acquired data is subject to systematic deviations and measurement noise influenced by external factors, such as intensity and incidence angle. Previous uncertainty modeling approaches often addressed these components independently. This research introduces a critical probabilistic regression framework for the joint estimation and calibration of TLS distance deviation and precision by leveraging advanced machine learning methods (NGBoost and residual neural network), assuming Gaussian distributed deviations. Initial work showed that systematic distance deviations are strongly influenced by intensity and incidence angle, and they can be effectively modeled using tree-based regressors like XGBoost, which achieved a coefficient of determination of 0.73. However, complex non-linear relationships and local context require more advanced methods. A modified PointNet deep learning approach was developed to incorporate the spatial context of the local point neighborhood, significantly outperforming XGBoost by achieving an approximate 16% improvement in RMSE on test data.

The current probabilistic model (NGBoost) was designed to predict the full Gaussian distribution of distance deviations, quantifying both the systematic deviation and precision (standard deviation) simultaneously. NGBoost demonstrated superior robustness compared to neural networks, especially in data-sparse regions, providing precision estimates that agree well with validated intensity-based reference models. The application of the residual neural network calibration model to unseen data reduced the standard deviation of residuals by 48% (e.g., from 0.69 mm to 0.36 mm in one case) and reduced the mean residual significantly (e.g., from 1.01 mm to -0.10 mm).

The findings reveal that the proposed ML approaches—especially the distribution-based

probabilistic models—provide a robust methodology for both TLS calibration and rigorous quantification of measurement uncertainty. Critical operational insights were derived: calibration models for systematic deviations are scanner-specific and cannot be reliably transferred across different TLS units of the same type. Conversely, precision models show good transferability and temporal stability. These advancements enhance the quality of TLS point clouds, serving as a critical complement to internal scanner calibrations and facilitating uncertainty-aware decision-making in high-accuracy engineering applications.