A Trajectory Consistency Metric for GNSS Anomaly Detection with LiDAR Odometry

Hans-Peter Wipfler[1] and Gerald Steinbauer-Wagner[1]

Abstract— **While Global Navigation Satellite System (GNSS)-based robot localization is successful in open scenarios, it quickly becomes unreliable in GNSS-degraded environments such as forests. With the increasing interest in using autonomous robots in forestry, it becomes more important to have reliable localization in forest environments, which are among the most challenging areas for GNSS-based localization. Having an estimate for the quality of the localization can help achieve this. While GNSS receivers provide uncertainty estimates based on signal characteristics and the satellites' constellation, practical experience shows that these values are less meaningful in forests. This paper presents an error metric that exploits the properties of commonly used robot localization setups to assess the quality of the localization. This assessment is based on a comparison between a LiDAR odometry-based local trajectory estimate and a GNSS-based global trajectory estimate in their respective coordinate systems. A qualitative analysis shows that the metric enables meaningful statements about the quality of position estimates derived from GNSS measurements in the global coordinate system.**

Index Terms— **anomaly detection, GNSS, LiDAR odometry**

I. INTRODUCTION

State estimation architectures of mobile robots often separate global and local state estimation for localization [6],[3]. This is done by using two world-fixed coordinate systems, a local coordinate frame that is locally consistent but suffers from long-term drift, and a global coordinate frame that is globally consistent but suffers from transient errors in GNSS-based position information. In forest environments, GNSS-based position estimation is heavily influenced by the surrounding environment due to signal shading and reflections caused by objects like trees or rock walls [2]. Even when the GNSS data is fused with IMU (Inertial Measurement Unit) data, practical experience has shown that these phenomena still have a large impact on the global position estimate [6]. However, many robots today are equipped with a LiDAR sensor, which can be used for local motion estimation and provides low-drift, locally consistent position estimates [5]. This work exploits the properties of local and global trajectories to detect patterns in the global trajectory that are not backed by the local trajectory. Based on this we developed a metric for assessing global localization quality, which allows monitoring of localization quality in real-time, making it usable for anomaly detection, adaptive sensor fusion, or GNSS rejection strategies.

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II. RELATED WORK

LiDAR-based odometry estimates the motion of a robot by aligning successive point clouds. Direct LiDAR Odometry (DLO) [1] is a computationally efficient approach that enables real-time LiDAR odometry on resource-constrained robotic platforms. One of the key features of the method is a submapping strategy that aims to keep the position estimate locally consistent. This makes it a reasonable choice for the use in local state estimation in forests.

In [7], the authors propose the use of trajectory similarity metrics for comparing a reliable short-term trajectory from motion estimation with an IMU with a trajectory obtained from GNSS measurements. These metrics compare only the similarity of the point sets. In contrast, the proposed approach computes its error value based on full transformations $\in SE(3)$. This allows the application of orientation- and translation-based error metrics.

III. METHODOLOGY

A. Localization Consistency Evaluation

To assess the reliability of GNSS-based localization in forest environments, we introduce a trajectory error metric that evaluates the consistency between local trajectories and global trajectories. Since the LiDAR odometry trajectory is locally consistent, it serves as a short-range reference. To achieve this, a relative pose error estimate between pose pairs from the global and local trajectories is used. To fully exploit the information contained in poses in $SE(3)$, an alignment of the trajectories is necessary to ensure that both position and orientation are compared meaningfully. In addition, the resulting error estimate should show a high sensitivity to the consistency of the most recent pose. In order to achieve this objective, each transformation used is related to this pose which is illustrated in Figure 1. For each evaluated pose, a subtrajectory is selected using a fixed spatial window defined by the parameters Δs_a and Δs_b where Δs_a defines the minimum look-back distance, ensuring that only sufficiently separated past poses are included, and Δs_b defines the maximum look-back distance, limiting the subtrajectory length to prevent excessive drift influence. Given a trajectory parameterized by the cumulative distance traveled s from the LiDAR odometry, the sub-trajectory consists of poses selected within the interval $[s-\Delta s_b, s-\Delta s_a]$. By choosing poses within this range, we ensure that the sub-trajectory captures the recent motion history while maintaining a stable reference for error computation. This results in three necessary steps that must be performed for each pose of interest: 1) subtrajectory selection: collect past poses within the interval $[s-\Delta s_b, s-$

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Δs_a], 2) alignment: align local and global subtrajectories to ensure a meaningful comparison of transformations, 3) error computation: compute the consistency error between both subtrajectories as defined below.

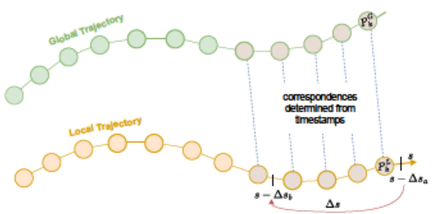

Fig. 1. Illustration of the trajectories used to compute the consistency error. The green poses are the poses of the trajectory of the robot in the global coordinate system. The orange poses are the poses of the robot in the local coordinate system. The global poses are related to the local ones based on time, meaning every P_k^L maps to a P_k^G.

B. *Error Metric Formulation*

The transformation from the current pose to the pose at $s-\Delta s$ in the aligned local trajectory is given by:

$$T^{L*}_{s-\Delta s,s} = \left(T^{L}_{\text{align}} \cdot P^{L}_{s-\Delta s}\right)^{-1} \cdot \left(T^{L}_{\text{align}} \cdot P^{L}_{s}\right), \tag{1}$$

where T^{L}_{align} is the transformation obtained in the alignment step, and P^{L}_{s} is the pose of the local trajectory at traveled distance s. The global trajectory is related to the local trajectory by the time $t(s)$, with poses defined as $P^{G}_{t(s)}$, and the corresponding transformation:

$$T^{G}_{t(s-\Delta s),t(s)} = \left(P^{G}_{t(s-\Delta s)}\right)^{-1} \cdot P^{G}_{t(s)}. \tag{2}$$

The relative transformation error is computed as:

$$E(\Delta s, s) = \left(T^{G}_{t(s-\Delta s),t(s)}\right)^{-1} \cdot T^{L*}_{s-\Delta s,s} \in \mathrm{SE}(3), \tag{3}$$

where any error metrics for SE(3), such as rotational or translational error, can be applied. To demonstrate the approach we employ the translational error according to [4]:

$$e_T(\Delta s, s) = \|trans(E(\Delta s, s))\| \in \mathbb{R}^{+}. \tag{4}$$

Finally, the consistency error is computed as:

$$\overline{e_T(s)} = \frac{1}{(\Delta s_b - \Delta s_a)} \int_{\Delta s_b}^{\Delta s_a} e_T(\sigma, s) \quad d\sigma \in \mathbb{R}^{+}. \tag{5}$$

$\overline{e_T(s)}$ represents a metric for the consistency of the local and global subtrajectory and consequently for the current quality of localization.

IV. Results

In the implementation, the integral for the consistency error from Equation 5 is approximated using the trapezoidal rule, performed on poses sampled over s for $\Delta s_a = 0$ and $\Delta s_b = 15m$. To evaluate the metric, we used data collected in a forest setting where the global trajectory was estimated using a *geo-konzept geo-kombi* INS/GNSS system, while the local trajectory was derived from DLO using data from a *Livox MID-360* LiDAR sensor. Figure 2 shows a part of a trajectory estimated by the GNSS system, where the value of $\overline{e_T(s)}$ is color coded. The robot moved along the middle of a forest road. The road shown in the underlying map can be used as a qualitative reference. It is clearly visible that the estimate of $\overline{e_T(s)}$ is high for obvious anomalies, while it is low for regions where the estimate is likely to be correct. This observation was further confirmed by analyzing the consistency error over a trajectory of more than $6km$, showing a strong correlation between high error estimates and significant GNSS inconsistencies.

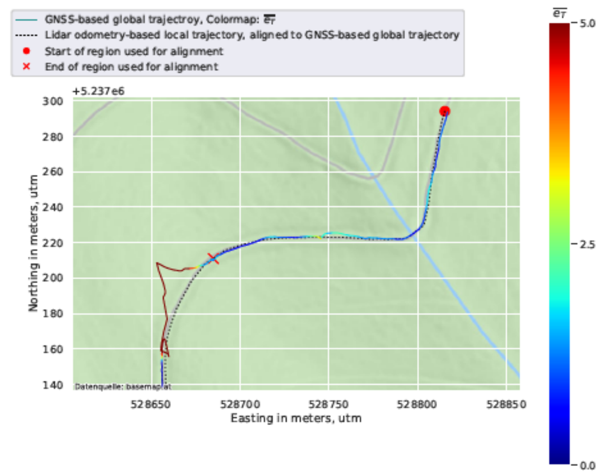

Fig. 2. Global GNSS-based trajectory estimate on a forest road with the corresponding consistency errors $\overline{e_T(s)}$ color coded. For visualization purposes, the local LiDAR odometry-based trajectory estimate is additionally shown, aligned to the global trajectory estimate using a selected region.

V. Conclusion

This work introduces a metric to assess the reliability of GNSS-based localization in forest environments. It compares local LiDAR odometry and global GNSS trajectories to enable real-time anomaly detection and localization quality monitoring. The metric provides a measure of localization data consistency that can be used for adaptive sensor fusion or GNSS rejection strategies. Future work will focus on evaluating this method in diverse environments and integrating it into state estimation frameworks for improved robustness.

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