Sensor Fusion-Based Motion Compensation in 3D LiDAR Point Clouds

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Abstract : *This paper presents a method for compensating motion-induced distortion in 3D LiDAR point cloud data using sensor fusion of Global Positioning System (GPS) and Inertial Measurement Unit (IMU) data. LiDAR sensors, which scan environments by rotating mirrors, often assume a static viewpoint. However, the motion of the ego vehicle introduces discrepancies between the assumed and actual viewpoints, leading to distorted point cloud data. To address this, our approach fuses accurate positioning data from GPS with high-frequency motion dynamics from IMU to estimate the vehicle's odometry. This data is aligned in the East-North-Up (ENU) coordinate frame and used to interpolate the vehicle's motion during each LiDAR scan. Each point in the point cloud is then adjusted based on the interpolated odometry to correct the distortions. Utilizing data from Udacity® recorded with GPS, IMU, camera, and LiDAR sensors, our method effectively reconstructs an accurate representation of the surroundings. This process is critical for applications such as autonomous driving and environmental modeling, where precise and reliable point cloud data are essential.*

Keywords:LiDAR, IMU, GPS, Sensor Fusion, Motion Compensation

Introduction

Sensor fusion-based motion compensation in 3D LiDAR point clouds is crucial for enhancing the accuracy of object detection and motion tracking in autonomous systems. Recent advancements leverage temporal data and multi-sensor integration to address motion distortion and improve performance. The TM3DOD method aggregates temporal LiDAR data to enhance 3D object detection by capturing motion features from consecutive point clouds. This approach significantly improves detection accuracy compared to traditional methods (Park et al., 2024). Qin et al., (2022) propose a method that utilizes LiDAR odometry to correct motion distortion in point clouds. By selecting uniform feature points and applying Euclidean clustering, their technique effectively reduces errors in SLAM algorithms. A multi-sensor approach combines LiDAR with IMUs to capture human motion accurately. This method optimizes local actions and corrects translation deviations, resulting in precise motion capture (Ren et al., 2023). Haas et al., (2023) developed a neural network to estimate object velocity from LiDAR data, addressing motion distortion without requiring sensor fusion. This method enhances tracking reliability.

In contrast, while these advancements show promise, challenges remain in achieving real-time processing and handling complex environments, which may limit their practical applications in dynamic scenarios.

One of the widely explored techniques in motion compensation is the fusion of LiDAR with IMU data. The IMU provides precise measurements of angular velocity and linear acceleration, which can be used to track the sensor's motion and adjust the LiDAR point cloud accordingly. Jiang et al., (2024) developed a sensor fusion algorithm that fuses LiDAR data with IMU measurements, enabling accurate motion compensation for mobile platforms like autonomous vehicles. Their approach used a Kalman filter to fuse the IMU and LiDAR data, demonstrating significant improvements in the accuracy of point clouds under dynamic conditions.

Similarly, Zhang & Singh, (2014) proposed a method combining LiDAR with visual odometry to address the issue of motion distortion. Their research employed a tightly coupled LiDAR-visual-inertial system to mitigate distortions during high-speed vehicle motion, particularly in GPS-denied environments. Their results showed substantial gains in localization accuracy compared to systems that only used LiDAR or visual odometry alone.

Kalman filtering is a popular statistical method used to fuse sensor data. It recursively estimates the state of a system, considering both the process model and sensor noise. One of the foundational works in this domain, by MAILKA et al., (2024), developed a Kalman filter-based sensor fusion framework that integrated LiDAR, GPS, and IMU data to perform motion compensation in dynamic environments. The framework significantly enhanced the robustness of the point clouds, particularly in urban driving conditions.

Chen et al., (2023) proposed an extended Kalman filter (EKF) to further enhance the fusion process between LiDAR and IMU sensors. Their EKF-based system could track non-linear movements more accurately, providing better motion compensation in real-time for autonomous drones and robots. The fusion of GPS, IMU, and LiDAR technologies is crucial for enhancing localization accuracy in autonomous vehicles, particularly in complex or challenging environments. Each sensor brings unique strengths to the table, compensating for the weaknesses of the others. GPS offers accurate positioning in open spaces but struggles in urban or indoor areas due to signal interference (Alaba, 2024). IMU provides continuous motion data and works well in GPS-denied environments, yet its accuracy degrades over time due to drift. LiDAR is excellent for detailed mapping and localization, though it can face challenges in feature-scarce environments (Gao et al., 2023). To maximize the benefits of these sensors, fusion techniques such as Kalman Filtering, including Unscented and Consensus Kalman Filters, and Factor Graph Optimization are employed. These methods enhance overall accuracy and robustness by reducing error accumulation and improving pose estimation (Alaba, 2024; Chen et al., 2023; Gao et al., 2023).

Effective fusion depends on precise sensor calibration and system resilience. Accurate calibration methods, such as two-step self-calibration, ensure that the sensor data aligns correctly, enhancing reliability (Nie et al., 2023). Additionally, resilience engineering evaluates how well the system recovers from disruptions, providing critical insights into the system's performance under different operating conditions (Fanas et al., 2023). Despite significant advancements, challenges remain in ensuring consistent localization performance in varying environments. Future research may focus on refining these fusion techniques and improving calibration methods to enhance the robustness and reliability of autonomous navigation systems further.

The study addresses a critical gap in the accurate utilization of LiDAR data for autonomous systems, particularly the challenge of motion-induced distortion caused by ego vehicle movement during LiDAR scans. Existing motion compensation techniques often rely solely on point cloud data, which proves inadequate for correcting distortions, especially during complex, high-speed vehicle motion. Additionally, while sensor fusion techniques involving GPS and IMU have been explored, there has been limited research on their integration for real-time point cloud correction, leaving a gap in achieving precise motion compensation. Furthermore, issues of alignment between GPS, IMU, and LiDAR data in a unified coordinate system complicate the compensation process. This study resolves these gaps by proposing a method that fuses GPS and IMU data to estimate ego vehicle motion and compensates for point cloud distortions, while ensuring all sensor data is aligned within a common vehicle coordinate system. This comprehensive approach significantly improves the accuracy and robustness of motion compensation, offering a practical solution for real-world autonomous driving applications.

The problem addressed in this study is the motion-induced distortion in LiDAR point cloud data caused by the movement of the ego vehicle during sensor scans. This distortion results in inaccurate environmental representations, which can hinder the performance of autonomous systems, particularly in dynamic driving scenarios. Current motion compensation methods, which either rely solely on point cloud data or lack effective sensor fusion techniques, fail to provide the precision needed for real-time correction of these distortions. The challenge lies in accurately estimating the vehicle's motion using data from multiple sensors (GPS and IMU), aligning this data in a unified coordinate system, and applying it to correct the point cloud. Solving this problem is essential for improving the accuracy and reliability of LiDAR-based perception in autonomous driving applications.

Methodology

The methodology for compensating motion-induced distortion in 3D LiDAR point clouds using sensor fusion begins with data acquisition and preparation. GPS, IMU, and LiDAR data are downloaded from the Udacity dataset, unzipped, and loaded into MATLAB. The LiDAR data is transformed from its original ENU frame to the vehicle ENU frame using a rigid transformation, while GPS and IMU data are aligned with the vehicle's coordinate system. LiDAR frames are selected for motion compensation, and GPS data is converted to the vehicle's ENU frame for consistency.

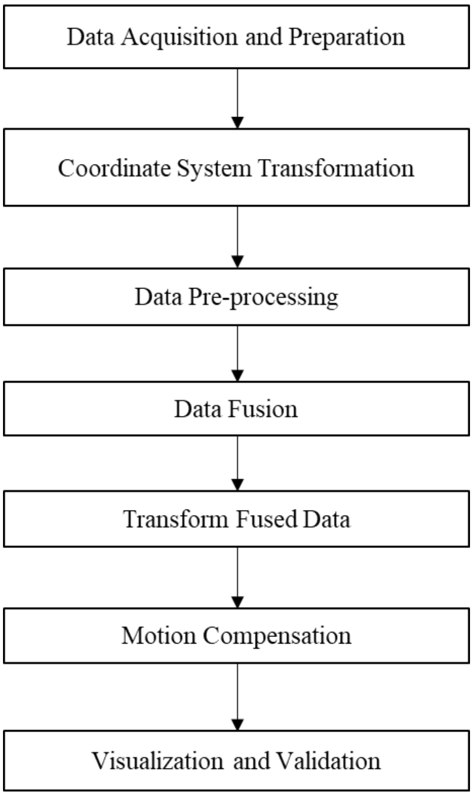

Figure 1: Methodology workflow.

The next step involves fusing GPS, IMU, and LiDAR data into a unified timetable, followed by applying a Kalman filter to fuse the GPS and IMU data, estimating the ego vehicle's position and orientation. This fusion process uses synchronized sensor data with initial states and measurement covariances, providing an accurate odometry estimate. The estimated ego vehicle odometry is transformed from the NED frame to the ENU frame, creating transformation objects representing the vehicle's pose at each LiDAR timestamp. Motion compensation is applied by estimating timestamps for each LiDAR point and computing the relative transformation between consecutive LiDAR frames. The undistortEgoMotion function corrects the distortion in the point cloud data based on these transformations. Figure 2 presents the coordinate transformation to a common coordinate system.

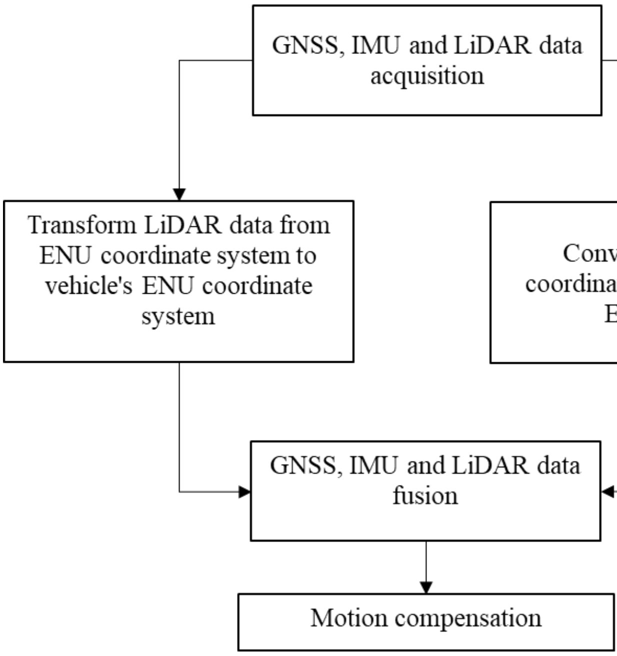

Figure 2: Coordinate transformation workflow.

Finally, the original and compensated point clouds are visualized to evaluate the effectiveness of the compensation, with the entire process looping through all selected LiDAR frames to ensure comprehensive correction of motion-induced distortions.

Results and Discussion

The diagram (Figure 3) illustrates the impact of motion compensation on point cloud data collected by a LiDAR sensor mounted on a moving vehicle. In this visualization, two distinct regions are highlighted: a green region representing the ground and a red region representing a signboard. The green region demonstrates how motion compensation has successfully corrected the distortion in the point cloud data related to the ground. This means that after adjusting for the ego vehicle's motion, the ground appears more accurately in the 3D LiDAR data, with reduced blurring or stretching.

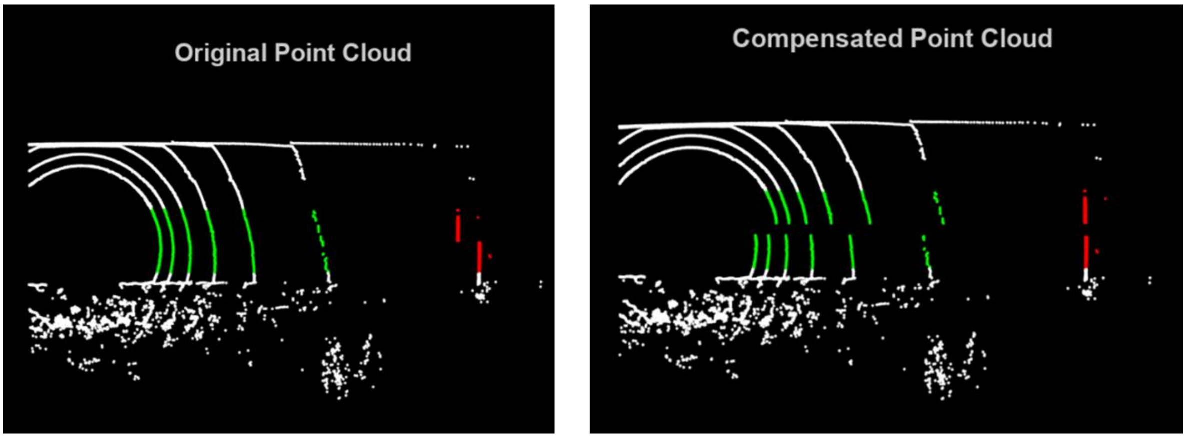

Figure 3: Original point cloud and motion compensated point cloud.

Similarly, the red region highlights the correction applied to the signboard. Without motion compensation, the signboard would appear distorted or misaligned due to the motion of the vehicle while the LiDAR sensor was scanning. After compensation, the points on the signboard are correctly aligned, and the structure appears clear and undistorted in the point cloud. This diagram effectively demonstrates the improvements in accuracy and fidelity achieved by compensating for the ego vehicle's movement during data collection.

The motion compensation was applied to multiple frames of the recorded LiDAR data, and the results demonstrated a significant improvement in the accuracy of the point cloud representation. In the original point cloud, distortions caused by the ego vehicle's motion were clearly visible, particularly in areas close to the ground and on vertical structures like signboards. Figure 4 illustrates the motion compensation applied to another frame of data.

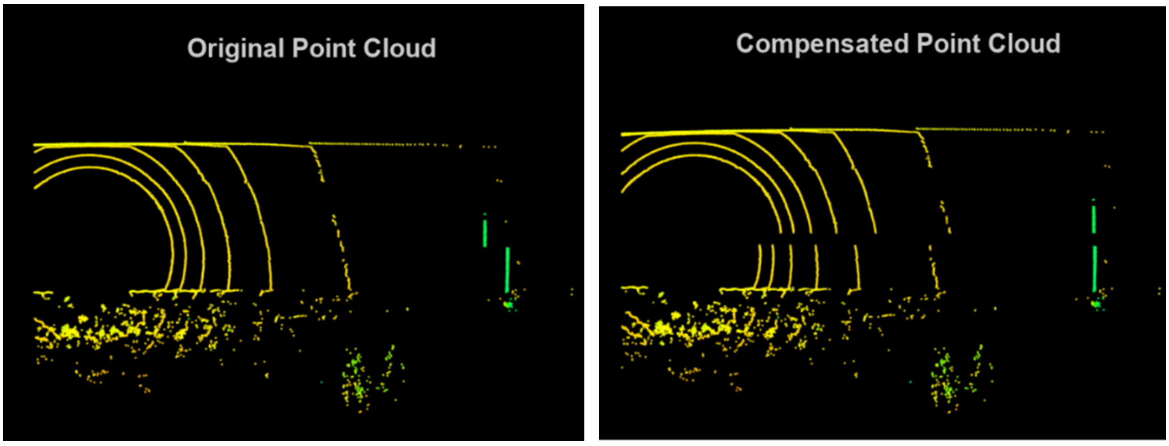

Figure 4: Original point cloud and motion compensated point cloud.

After applying motion compensation, the corrected point cloud displayed much smoother and more coherent surfaces. The ground region, highlighted in green, showed less distortion, while vertical structures such as signboards, represented in red, were corrected to appear more consistent and aligned. These results confirm that motion compensation effectively mitigates motion-induced errors, resulting in a more accurate depiction of the environment. Figure 5, presents the different scenario of the data when applied with the motion compensation technique.

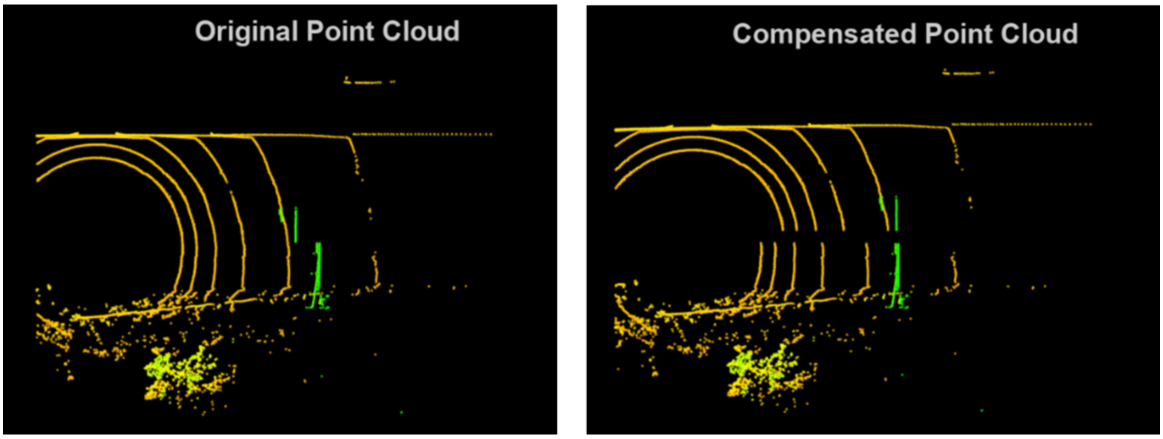

Figure 5: Original point cloud and motion compensated point cloud.

Conclusion and Recommendation

This study successfully demonstrates the effectiveness of sensor fusion, combining GPS and IMU data, to compensate for motion-induced distortion in LiDAR point cloud data collected from a moving ego vehicle. By aligning the data in the ENU coordinate system and applying motion compensation algorithms, the research effectively corrected distortions caused by vehicle movement. The results highlight significant improvements in the accuracy of point cloud representations, especially for ground surfaces and vertical structures. These enhancements are critical for autonomous driving applications, where precise environmental perception is essential for safe and reliable navigation.

Future work could focus on implementing real-time motion compensation algorithms to further improve the operational efficiency of autonomous vehicles. Expanding the sensor fusion approach to include additional sensors, such as cameras and radar, may improve robustness in challenging environments like adverse weather conditions. Additionally, exploring motion compensation for vehicles operating on uneven or off-road terrains could provide valuable insights. Optimizing the computational efficiency of these algorithms for low-power systems is another potential area of research. Lastly, integrating deep learning models to further refine and correct point cloud data could lead to even higher accuracy in understanding the vehicle's surroundings.

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