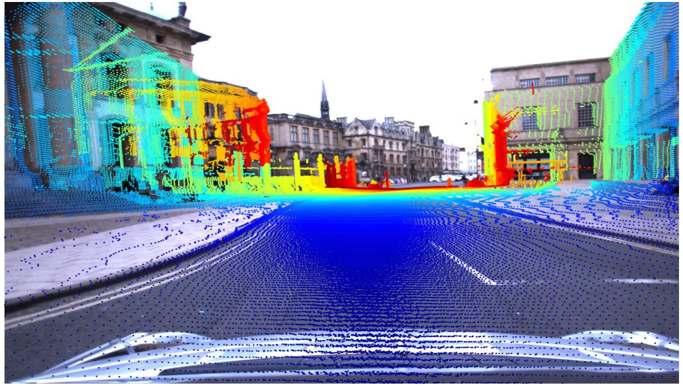
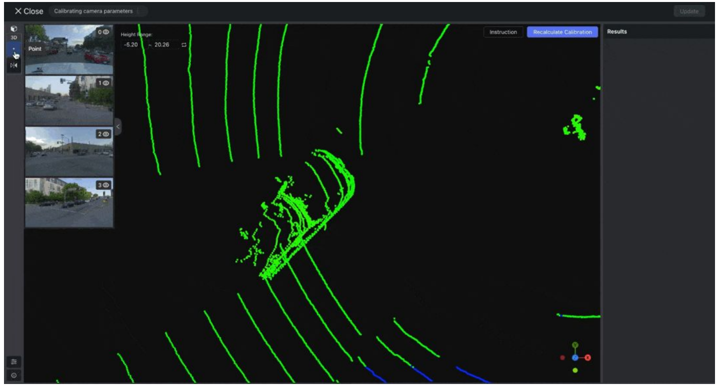
On the fly camera and Lidar (timing calibration)

Samara Holmes, Hemanth Tekumalla, Nishad Milind Rajhans, Kaushik Deo

Introduction

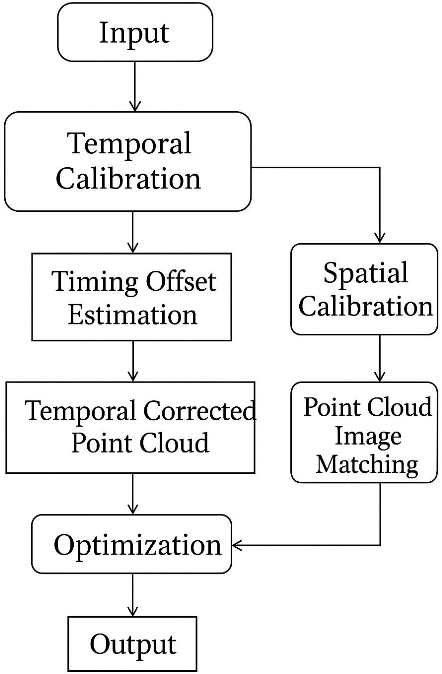
- **Temporal calibration** is the process of estimating and correcting the **time offset** between two sensors, such as a LiDAR and a camera, so that measurements from both sensors correspond to the **same real-world moment.**
- Aligns the timestamps of asynchronous sensors (LiDAR + camera) by estimating the time offset δt\delta tδt, ensuring that both sensors observe the scene at the same physical moment.
- Camera and LiDAR operate at different frequencies and may have unknown time offset et between the stamps.
- Temporal misalignment degrades multi-sensor fusion for detection, tracking, and SLAM, since objects move between the camera and LiDAR exposures.





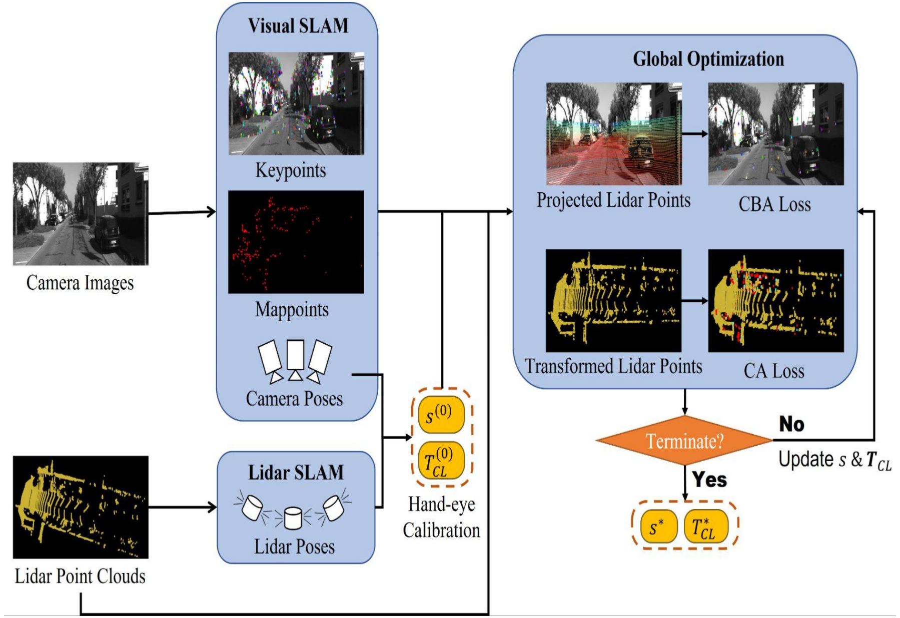
Optimization Flowchart

- The camera captures frames instantly, while the LiDAR scans points over time, causing their timestamps to be misaligned.
- A temporal offset exists between the LiDAR and camera clocks, meaning they observe the same scene at different moments. Because LiDAR beams fire sequentially, incorrect timestamps cause warped point clouds during motion.
- Temporal calibration computes the correct time shift between sensors by comparing LiDAR motion with camera motion or image features.
- Each LiDAR point is re-timestamped and motion-compensated using the estimated δt\delta tδt to produce a synchronized point cloud.
- Once timestamps align, LiDAR points project correctly into camera images, enabling accurate spatial calibration, mapping, and SLAM.



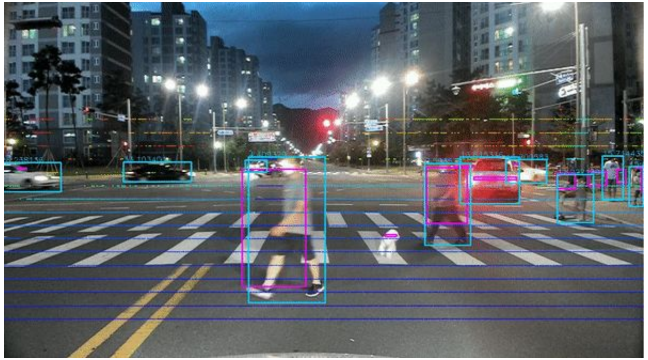
Methodology

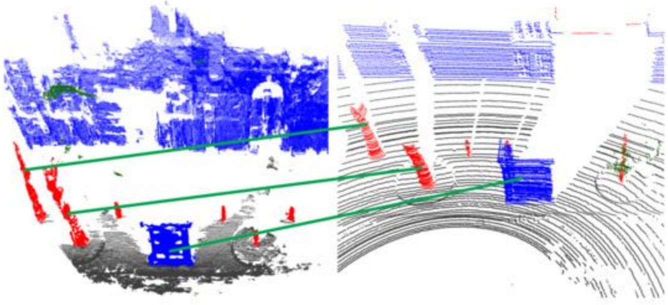
- The camera and LiDAR operate asynchronously, so Visual SLAM and LiDAR SLAM generate pose trajectories at different timestamps.
- This timing mismatch causes the same real-world features to appear misaligned when LiDAR points are projected onto camera images.
- The system begins with an initial hand-eye calibration, but temporal offset δt\delta tδt must still be estimated for proper synchronization.
- During global optimization, LiDAR points are time-corrected, transformed, and projected into the camera frame to evaluate alignment errors.
- The optimizer adjusts δt\delta tδt to minimize CBA Loss and CA Loss, progressively aligning sensor observations in time.
- Once the losses converge, the final calibrated temporal offset ensures accurate, distortion-free fusion between LiDAR scans and camera images.



Projecting LiDAR TO IMAGE

- For dynamic Object handling buid a K-d tree on point cloud at time t and match nearest neighbour from the time t+et,
- For temporal alignment score, define score weighted sum of grayscale (inverse distance) values where projected horizontal and vertical LiDAR line points land on the image, Horizontal lines use weighted w, Te is LiDAR-camera calibration Transform, Tv is motion between times.
- For candidate transform T=TeTv corresponding to a hypothesized temporal alignment, map LiDAR points P into camera coordinates, $P_i^C = R_{L\to C} P_i^L + t_{L\to C}$
- Decompose: $T_e = T_e' + \epsilon_e, T_v = T_v' + \epsilon_v$. Error Term: $T_e' \epsilon_v + T_v' \epsilon_e$ captures calibration and motion estimation error affected by temporal alignment,



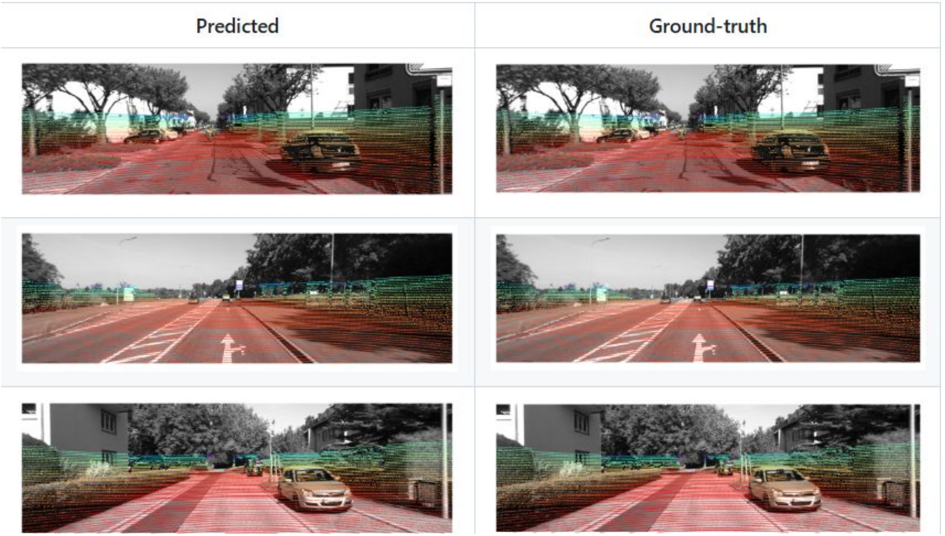


a) SfM point cloud

b) Lidar point cloud

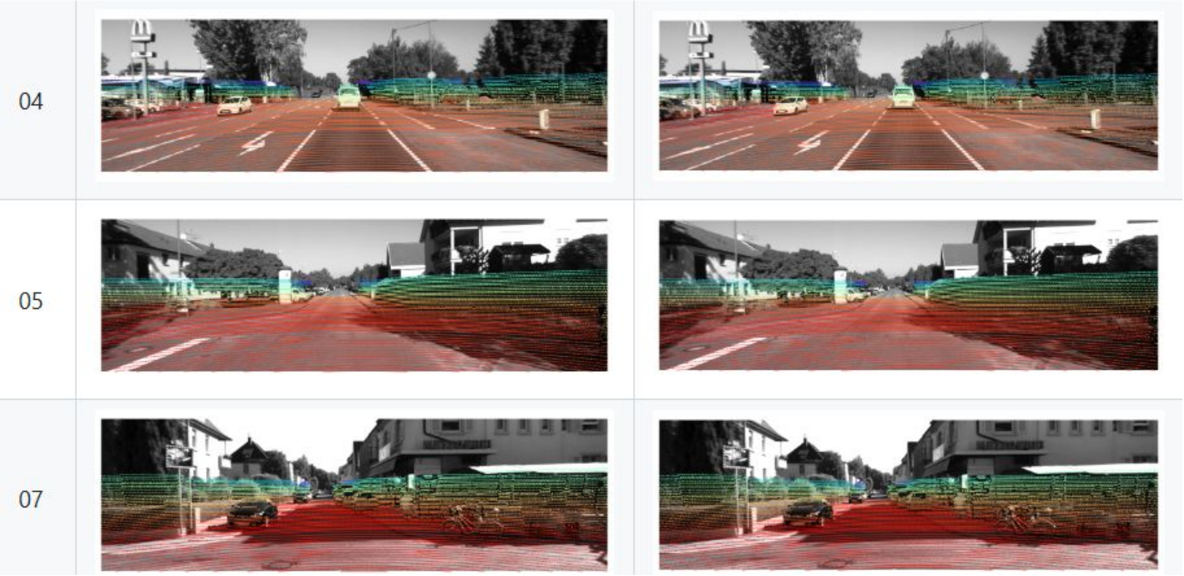
Performance on KITTI Odometry

- Use KITTI dataset with HDL-64E LiDAR (10 Hz) and high-resolution camera; ground-truth and timestamps from KITTI calibration files.
- Emulate an asynchrony scenario: point cloud frequency 5 Hz, image and inertial navigation 10 Hz, and LiDAR frames delayed by 0.1 s relative to images.
- Under 5 Hz LiDAR and 10 Hz image/IMU, the proposed method achieves lower average Euclidean distance than ROS soft synchronization across multiple sequences.
- Reported improvement in Euclidean-distance-based metric is about 38.5% over the ROS message filter method, demonstrating effective on-the-fly temporal correction.
- Rotation units: degree
- Translation units: cm
- Accuracy reserved to 0.01



Sequence	Roll	Pitch	Yaw	tX	tY	tZ	Rotation RMSE	Translation RMSE
00	-0.12	-0.22	-0.07	2.93	1.59	0.18	0.26	3.33
02	-0.01	-0.25	-0.16	-2.80	1.63	1.18	0.29	3.45
03	-0.08	-0.10	-0.09	-3.25	3.23	1.22	0.15	4.74

Result



Sequence	Roll	Pitch	Yaw	tX	tY	tZ	Rotation RMSE	Translation RMSE
04	0.01	-0.09	0.05	1.03	-0.19	1.10	0.11	1.52
05	0.01	-0.19	-0.15	1.95	1.56	-0.54	0.24	2.56
07	-0.05	-0.00	-0.20	1.07	2.07	0.14	0.21	2.34

Result

This point-cloud represents the **3D geometric structures** that a LiDAR sensor captures during operation. It mimics the type of line and plane features used in the research paper for **Camera–LiDAR spatial calibration**.

Shows the 3D structure captured by the sensor, including vertical and horizontal edges and dynamic objects. These line features are extracted and used as geometric constraints in the calibration algorithm. Their consistency makes them ideal for aligning the LiDAR frame with the camera frame

LiDAR does not capture a full scan at one instant, each laser beam fires at a slightly different time. If the system clock is not aligned with the camera's timing, objects appear distorted or duplicated. This visualization shows how temporal misalignment affects 3D geometry and why correcting the timing offset is critical for accurate calibration.