Multi-Sensor Sequential Calibration System at TuSimple

- 1. Introduction
- 2. Problem Constraints
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- 5. Evaluation



Impact. Delivered in time for a demo of the autonomous driving technology.





1. Introduction: 2. Operational Design Domain

- L4 autonomous truck
- Highway, limited urban driving
- Mapped roads
- Routes are known a priori
- The same routes are repeatedly driven



1. Introduction: 3. Extrinsic Camera Calibration

Uncalibrated

The goal is accurate SE(3) intersensor camera transforms

Calibrated

Projection of a prior map onto an image







2. Problem Constraints: 1. Calibration Environment



2. Problem Constraints: 2. Operations

- A defined, pre-mapped calibration route.
- The vehicle is operated by a licensed driver
- Data collection
- Offline, batch optimization for extrinsic calibration

Example route





2. Problem Constraints: 3. Priors

Camera Extrinsic Priors

Camera Intrinsics

$$^{cam_c}\hat{T}_{imu} \in SE(3)$$

$$K = egin{pmatrix} f_x & 0 & c_x \ 0 & f_y & c_y \ 0 & 0 & 1 \end{pmatrix}$$

$$D = k_1, k_2, k_3, k_4$$

RTK GPS



Lane Map



Detections



3. Basic Model: 1. Where we're headed T_2 Tn T₁ • • • **X**2 X_1 Xn **X**3 bn **b**₂ **b**₃ D_1 Vn V2 **V**3 Variables Factors $T_c \in SE(3)$ Identity prior camera extrinsic IMU preintegration $x_t \in SE(3)$ vehicle state GNSS pose prior 3D-2D projection velocity prior 2D-2D epipolar line IMU bias

 $b_t \in \mathbb{R}^6$ $v_t \in \mathbb{R}^3$

velocity





3. Basic Model: 2. Mathematical Description

Projection Equation

 $p_m^c = K \ ^{cam_c} T_{veh} \ ^{veh} T_{enu} \ P_m$

 $P_m \in \mathbb{R}^3$ $p_d^c \in \mathbb{R}^2$ map point detected 2D point $^{veh}T_{enu} \in SE(3)$ vehicle pose From e.g., nearest neighbors data association $^{cam_c}T_{veh} \in SE(3)$ camera extrinsic $K \in \mathbb{R}^{3 \times 3}$ pinhole camera intrinsic $p_m^c \in \mathbb{R}^2$ projected map point

Residual

$$p_d^c - p_m^c$$



3. Basic Model: 3. Stationary Formulation



 $\underset{(T_{c})_{c \in C}}{\operatorname{argmin}} \sum_{c \in C} \sum_{(d,m)_{c}} \frac{1}{2} |p_{d}^{c} - h_{m}(T_{c})|_{\Sigma_{m}}^{2}$



measurement covariance



3. Basic Model: 4. Factor Graph



Variables T_c

Factor Graph





4. Extensions: 1. Robust Noise Model

$\underset{(T_c)_{c \in C}}{\operatorname{argmin}} \sum_{c \in C} \sum_{c \in C} \tau(|p_d^c - h_m(T_c)|_{\Sigma_m})$

 $\tau()$

robust loss function



4. Extensions: 2. Epipolar Constraint



4. Extensions: 3. Sequential Model

- Essential matrix constraint between front and rear facing cameras.
- Capture more data from different viewpoints.
- Add vehicle state variables for robustness to GPS noise and bias.





4. Extensions: 4. IMU Preintegration

- "Preintegration" avoids recomputing the update for each linearization point
- The IMU bias and the vehicle velocity are added to the model.

Variables

- $T_c \in SE(3)$
- $x_t \in SE(3)$
- $b_t \in \mathbb{R}^6$
- $v_t \in \mathbb{R}^3$





4. Extensions: 5. Rolling Shutter Compensation



- Calculate the scan line time using the readout offset and the exposure.
- Interpolate the camera pose for the scan line time for each constraint



5. Evaluation: 1. Metrics

- Residuals. Low in terms of the number of residuals.
- Visual inspection. Accurate alignment quality of multiple cameras.
- Runtime. Two orders of magnitude faster than the previous approach due to the use of an optimization library that exploits sparsity.
- Amount of data. Use the subset of data required for the extrinsic calibration to stabilize.
- Extensible software design. The same implementation was seamlessly applied to different trucks with different camera configurations.



5. Evaluation: 2. Limitations

- Different accuracy in roll, pitch, and yaw
- Data association can be difficult in the long-range camera.
- Multiple sources of error
 - Detection accuracy
 - GPS accuracy
 - Fidelity in map points
 - Perceptual aliasing in data association
 - Extrinsic jitter due to vehicle motion

a association cle motion



Questions?