Degeneration-aware Outlier Mitigation for Visual Inertial Integrated Navigation System in Urban Canyons

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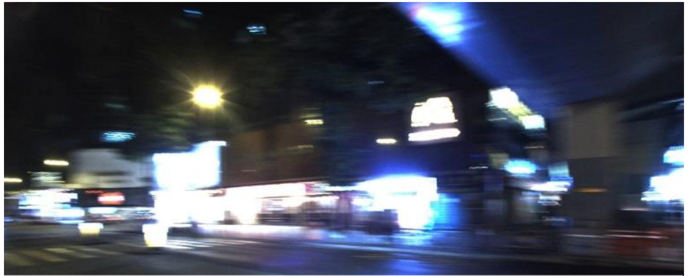
Challenges of Positioning in Urban Areas

Moving objects!
Dense traffic!

Key problem 1: Dynamic object degrades the **visual** positioning!



Key problem 2: Poor illumination condition degrades the feature detection and tracking

IMU is subject to severe drift in dense traffic scenarios!

Dynamic object degrades the visual positioning!

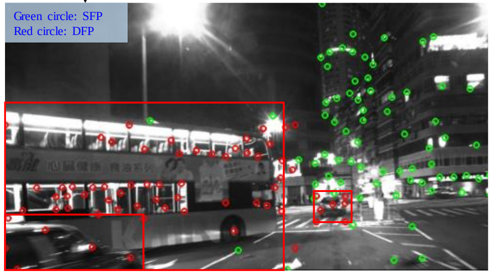
[1] Sun, Pei, et al. "Scalability in perception for autonomous driving: Waymo open dataset." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020.

Research Track to Solve the Key Problems

2019

Performance Analysis of VINS in Typical Urban Scenarios of Hong Kong. *Proceedings of APCAT* 2019, Taiwan.

Found out the problems of VINS in dynamic urban canyons



2020

Perception-aided Visual-Inertial Integrated Positioning in Dynamic Urban Areas. (*2020 IEEE/ION Position, Location and Navigation Symposium*)

Detect dynamic object and remodel dynamic features

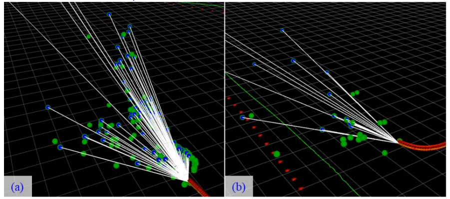
Model the uncertainty of features and improve the robustness

Robust Visual-Inertial Integrated Navigation System Aided by Online Sensor Model Adaption for Autonomous Ground Vehicles in Urban Areas." *Remote Sensing* 12.10 (2020): 1686

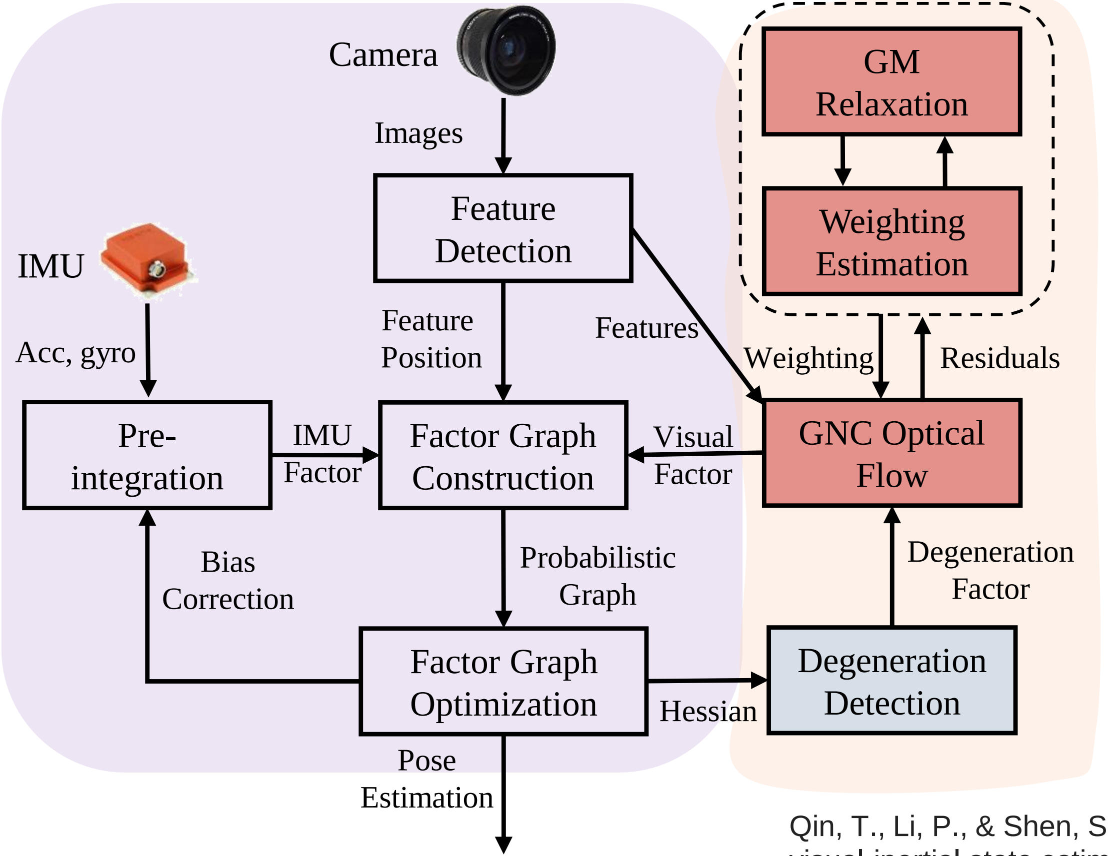
2021

Bai X, Wen W, Hsu L T. Degeneration-Aware Outlier Mitigation for Visual Inertial Integrated Navigation System in Urban Canyons[J]. IEEE Transactions on Instrumentation and Measurement, 2021, 70: 1-15.

Improve the features quality and mitigate the degeneration



Degeneration-aware Outlier Mitigation for VINS



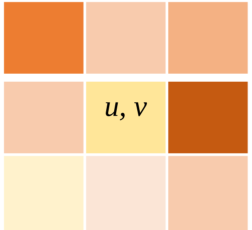
GM: the **G**eman **M**cClure function

Iteratively estimate the optical flow and estimate **the optimal weightings** of feature correspondences

How to detect degeneration?

Qin, T., Li, P., & Shen, S. (2018). Vins-mono: A robust and versatile monocular visual-inertial state estimator. *IEEE Transactions on Robotics*, *34*(4), 1004-1020.

Traditional Optical Flow



KLT (Kanade-Lucas-Tomasi) -Optical flow[1] : Two-frame difference optical flow estimation algorithm.

- Constant brightness
- Short-distance (short-term) movement
- Spatial consistency

$$I(u,v,t) = I(u+du, v+dv, t+dt)$$

First-order Taylor expansion:

$$I(u+du, v+dv, t+dt) = I(u,v,t) + \frac{\partial I}{\partial u}du + \frac{\partial I}{\partial v}dv + \frac{\partial I}{\partial t}dt$$

$$\frac{\partial I}{\partial u}\frac{u}{dt} + \frac{\partial I}{\partial v}\frac{v}{dt} = -\frac{\partial I}{\partial t}$$

$$I_u \quad u_t \quad I_v \quad v_t \qquad I_t$$

Only one equation but two unknown variables

$$\begin{bmatrix} I_{u1} & I_{v1} \\ I_{u2} & I_{v2} \\ \vdots & \vdots \\ I_{ui} & I_{vi} \end{bmatrix} \begin{bmatrix} \Delta u \\ \Delta v \end{bmatrix} = -\begin{bmatrix} I_{t1} \\ I_{t2} \\ \vdots \\ I_{ti} \end{bmatrix}, i \in (1, n \times n)$$

$$\begin{bmatrix} \Delta u \\ \Delta v \end{bmatrix} = \left(\mathbf{A}^{\mathrm{T}}\mathbf{A}\right)^{-1}\mathbf{A}^{\mathrm{T}}(-b)$$

with $\mathbf{A} = \begin{bmatrix} I_{u1} & I_{v1} \\ I_{u2} & I_{v2} \\ \vdots & \vdots \\ I_{ui} & I_{vi} \end{bmatrix} b = \begin{bmatrix} I_{t1} \\ I_{t2} \\ \vdots \\ I_{ti} \end{bmatrix}$

$$\begin{bmatrix} \Delta u \\ \Delta v \end{bmatrix} = \begin{bmatrix} \sum_i I_{ui}^2 & \sum_i I_{ui}I_{vi} \\ \sum_i I_{vi}I_{ui} & \sum_i I_{vi}^2 \end{bmatrix}^{-1} \begin{bmatrix} -\sum_i I_{ui}I_{ti} \\ -\sum_i I_{vi}I_{ti} \end{bmatrix}$$

[1] Beauchemin, Steven S., and John L. Barron. "The computation of optical flow." *ACM computing surveys (CSUR)* 27.3 (1995): 433-466.

Graduated Non-Convexity (GNC) Method

Original cost function:

$$X^* = \text{argmin} \sum_k r^2(y_k, x)$$

Black-Rangarajan Duality[1]

$$X^* = \text{argmin} \sum_k \rho(r(y_k, x))$$

$$X^* = \text{argmin} \sum_k [\omega_i r^2(y_k, x) + \Phi_{\rho_\mu}(\omega_i)]$$

Typical cost function

Outlier Process

Outlier process GNC-Geman McClure

$$\Phi_{\rho_\mu}(\omega_i) = \mu c^2(\sqrt{\omega_i} - 1)^2$$

Alternating Minimization

State Update: fixed weighting ω_i, optimize state $\mathbf{x}$

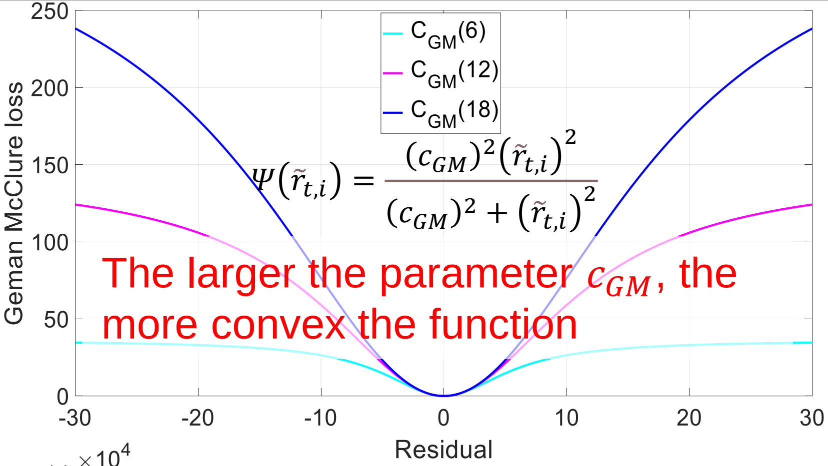
- Originally is a convex optimization problem
- The initial guess is given from last iteration.

Weight Update: fixed state $\mathbf{x}$, optimize weighting ω_i

- Solved in closed-form

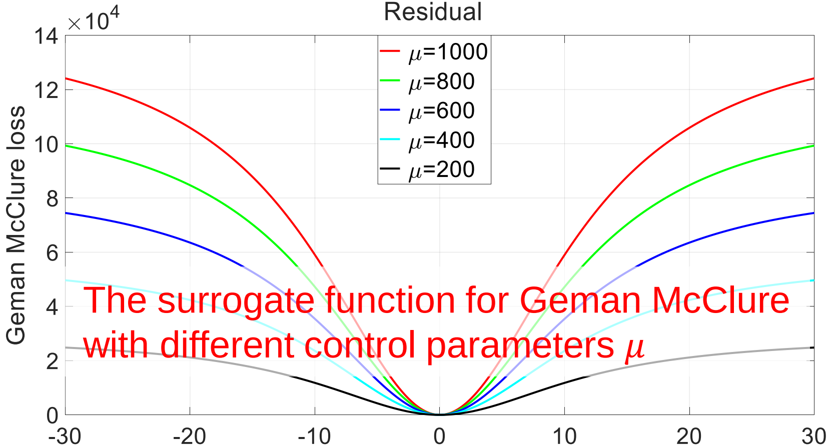
[1] Yang, Heng, et al. "Graduated non-convexity for robust spatial perception: From non-minimal solvers to global outlier rejection." IEEE Robotics and Automation Letters 5.2 (2020): 1127-1134.

Graduated Non-Convexity (GNC) Optical Flow



$$\Psi(\tilde{r}_{t,i}) = \frac{(c_{GM})^2(\tilde{r}_{t,i})^2}{(c_{GM})^2 + (\tilde{r}_{t,i})^2}$$

The larger the parameter c_{GM}, the more convex the function



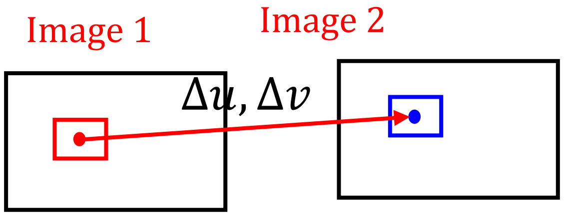
The surrogate function for Geman McClure with different control parameters μ

$$\min_{\Delta u^*, \Delta v^*} \sum_{i=1}^{n^2} \left(\rho \left(\left\| r\left(\boldsymbol{\Omega}_{t,i}, \begin{bmatrix} \Delta u \\ \Delta v \end{bmatrix}\right) \right\|_{\sigma_t^i} \right) \right)$$

$$\min_{\Delta u^*, \Delta v^*, \omega_{t,i} \in \boldsymbol{w}} \sum_{i=1}^{n^2} \left(\omega_{t,i} \left\| r\left(\boldsymbol{\Omega}_{t,i}, \begin{bmatrix} \Delta u \\ \Delta v \end{bmatrix}\right) \right\|_{\sigma_t^i}^2 + \phi_{\rho_\mu}(\omega_{t,i}) \right)$$

Typical Optical Flow

Outlier Process



Graduated Non-Convexity (GNC) Optical Flow

$$\min_{\Delta u^*, \Delta v^*, \omega_{t,i} \in \mathcal{W}} \sum_{i=1}^{n^2} \left(\omega_{t,i} \left\| r\left(\boldsymbol{\Omega}_{t,i}, \begin{bmatrix} \Delta u \\ \Delta v \end{bmatrix}\right) \right\|_{\sigma_t^i}^2 + \phi_{\rho_\mu}(\omega_{t,i}) \right)$$

$$\phi_{\rho_\mu}(\omega_{t,i}) = \mu {c_{GM}}^2 \left(\sqrt{\omega_{t,i}} - 1\right)^2$$ [1]

$$\omega_{t,i} < \omega_{thresh}, \omega_{t,i} \in \mathcal{W}$$

Optimize the GNC-OF problem:

Step1. Initialization:

$$\omega_{t,1}, \omega_{t,2}, \cdots, \omega_{t,i}\ , \omega_{t,i} \in \mathcal{W}$$

Step2. Variable update (weighting fixed):

$$\min_{\Delta u^*, \Delta v^*, \omega_{t,i} \in \mathcal{W}} \Sigma_{i=1}^{n^2} \left(\omega_{t,i} \tilde{r}_{t,i}^2 + \phi_{\rho_\mu}(\omega_{t,i}) \right)$$

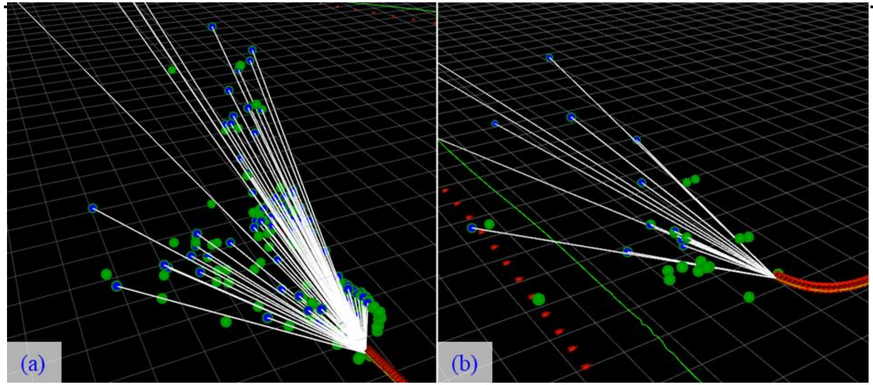
Step3. Weight update (variable fixed):

$$\omega_{t,i} = \left(\frac{\mu {c_{GM}}^2}{\tilde{r}_{t,i}^2 + \mu {c_{GM}}^2} \right)^2$$

Step4. $\mu = \frac{\mu}{1.4}$, repeat Steps 2 to 4, until $\mu = 1$.

[1] Yang, Heng, et al. "Graduated non-convexity for robust spatial perception: From non-minimal solvers to global outlier rejection." IEEE Robotics and Automation Letters 5.2 (2020): 1127-1134.

Degeneration Detection and Alleviation



Detect degeneration using Eigen values of Jacobian!

$$\frac{\partial \mathrm{r}_{\mathcal{C}}^{l}}{\partial \delta \mathbf{p}_{b_j}^{w}} = -\mathbf{R}_b^c \mathbf{R}_w^{b_j} \qquad \frac{\partial \mathrm{r}_{\mathcal{C}}^{l}}{\partial \delta \mathbf{q}_{b_j}^{w}} = \mathbf{R}_b^c$$

$$\mathbf{H}_{\mathcal{C}} = \begin{bmatrix} \mathbf{H}_{j,0}^{e} \\ \vdots \\ \mathbf{H}_{j,E}^{e} \end{bmatrix} \qquad \mathbf{H}_{\mathcal{C}}^{\mathrm{T}} \mathbf{H}_{\mathcal{C}} = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^{T}$$

$$\boldsymbol{\lambda} = [\lambda_1 \quad \lambda_2 \quad \lambda_3 \quad \lambda_4 \quad \lambda_5 \quad \lambda_6]^{T}$$

$$D_{\lambda} = \|\lambda_{min} - \lambda_{thresh}\|, \text{ with } \lambda_{min} < \lambda_{thresh}$$

$$\mathbf{H}_{j,l}^{e} = \begin{bmatrix} \frac{\partial \mathrm{r}_{\mathcal{C}}^{l}}{\partial \delta \mathbf{p}_{b_e}^{w}} & \frac{\partial \mathrm{r}_{\mathcal{C}}^{l}}{\partial \delta \mathbf{q}_{b_e}^{w}} \\ \frac{\partial \mathrm{r}_{\mathcal{C}}^{l}}{\partial \delta \mathbf{p}_{b_j}^{w}} & \frac{\partial \mathrm{r}_{\mathcal{C}}^{l}}{\partial \delta \mathbf{q}_{b_j}^{w}} \end{bmatrix}$$

$$\frac{\partial \mathrm{r}_{\mathcal{C}}^{l}}{\partial \delta \mathbf{p}_{b_e}^{w}} = \mathbf{R}_b^c \mathbf{R}_w^{b_j}$$

$$\frac{\partial \mathrm{r}_{\mathcal{C}}^{l}}{\partial \delta \mathbf{q}_{b_e}^{w}} = -\mathbf{R}_b^c \mathbf{R}_w^{b_j} \mathbf{R}_{b_e}^{w} \left(\mathbf{R}_c^b \frac{1}{\lambda_l} \hat{\bar{p}}_l^{c_e} + \mathbf{p}_c^b \right)^{\wedge}$$

How to mitigate degeneration?

Jacobian Matrix

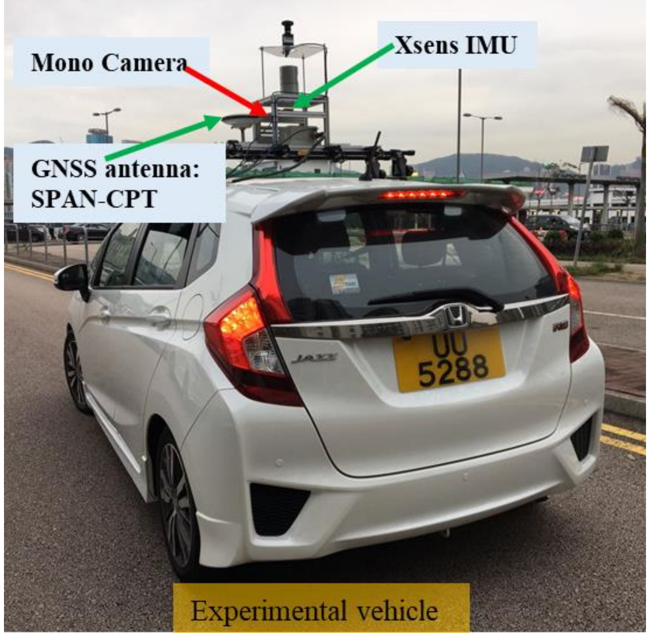
$$\mathrm{r}_{\mathcal{C}}\left(\hat{\mathrm{Z}}_l^{c_j}, \chi\right) = (\hat{\bar{p}}_l^{c_j} - \bar{p}_l^{c_j})$$

$$\mathrm{P}_l^{c_j} = \mathbf{R}_b^c(\mathbf{R}_w^{b_j}(\mathbf{R}_{b_i}^{w}(\mathbf{R}_c^b \frac{1}{\lambda_l} \pi_c^{-1}(\begin{bmatrix} \hat{u}_l^{c_i} \\ \hat{v}_l^{c_i} \end{bmatrix}) + \mathbf{p}_c^b) + \mathbf{p}_{b_i}^{w} - \mathbf{p}_{b_j}^{w}) - \mathbf{p}_c^b)$$

$$N_f^{*} = N_f + \frac{D_{\lambda}}{10}, \text{ with } \lambda_{min} < \lambda_{thresh}$$

Experimental Results

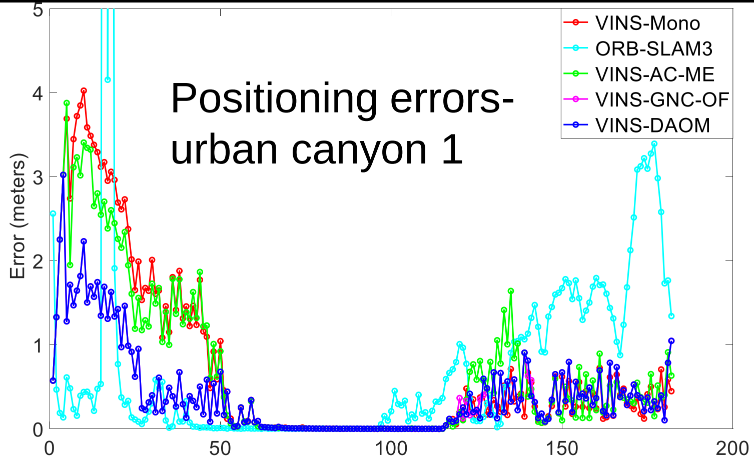
VINS-Mono : The original VINS solution from [9].
ORB-SLAM3: The ORB features are employed for visual feature detection and association.
VINS-AC-ME [13]: VINS aided by adaptive covariance estimation and adaptive M-estimator in our previous work
VINS-GNC-OF: The visual outlier rejection in the front end using the proposed GNC in this paper (first contribution in this work)
VINS-DAOM: The proposed degeneration-awareness outlier mitigation for VINS, Note that the proposed optical flow, GNC-OF, is included in the front-end of this method.



Experimental Results

Positioning performance in urban canyon 1

Items	VINS-Mono	ORB-SLAM3	VINS-AC-ME	VINS-GNC-OF	VINS-DAOM
MEAN (m)	0.71	0.86	0.71	0.45	0.40
FPE (m)	86.09	71.52	65.38	51.63	51.63
STD (m)	0.98	2.26	0.86	0.54	0.46
Max (m)	4.03	23.82	3.88	3.02	3.02
Improvement%			0%	36.6%	43.6%



Rotation performance in urban canyon 1

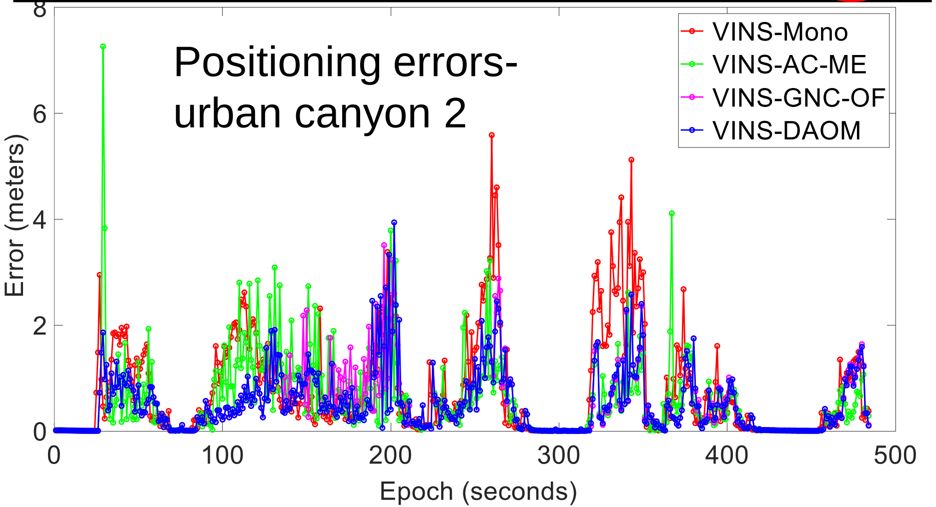
Items	VINS-Mono	ORB-SLAM3	VINS-AC-ME	VINS-GNC-OF	VINS-DAOM
MEAN (°)	0.89	2.04	0.84	0.89	0.87
FPE (°)	8.42	255.98	7.59	7.46	7.46
STD (°)	0.94	11.09	0.85	0.98	0.90
Max (°)	4.81	119.86	4.77	6.79	4.80
Improvement%			4.82%	0.22%	2.13%

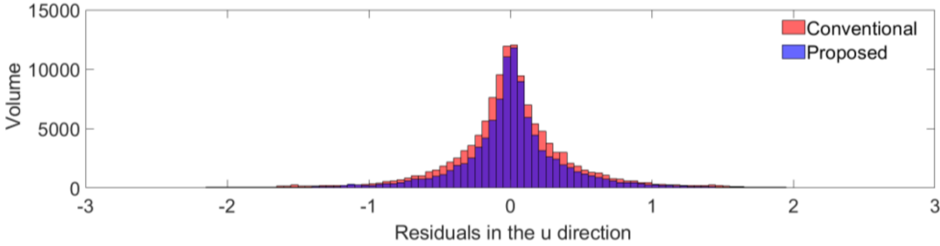
The rotation usually offers **better constraints** with the help of the gyroscope sensor inside the employed IMU sensor

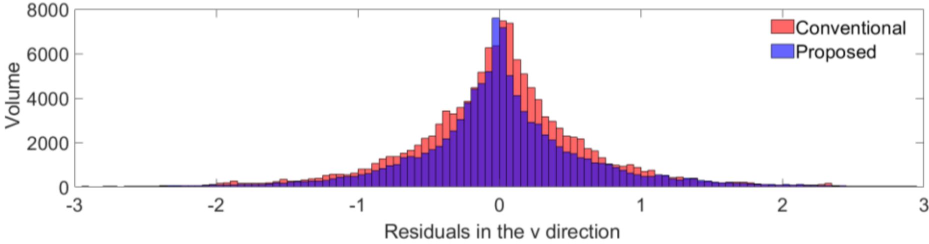
FPE: the final total positioning error

Experimental Results

Items	VINS-Mono	ORB-SLAM3	VINS-AC-ME	VINS-GNC-OF	VINS-DAOM
MEAN (m)	0.79	Fail	0.59	0.54	0.52
FPE (m)	38.81	Fail	81.79	36.91	37.20
STD (m)	0.96	Fail	0.75	0.60	0.58
Max (m)	5.58	Fail	7.26	3.51	3.94
Improvement%			25.3%	31.6%	34.2%



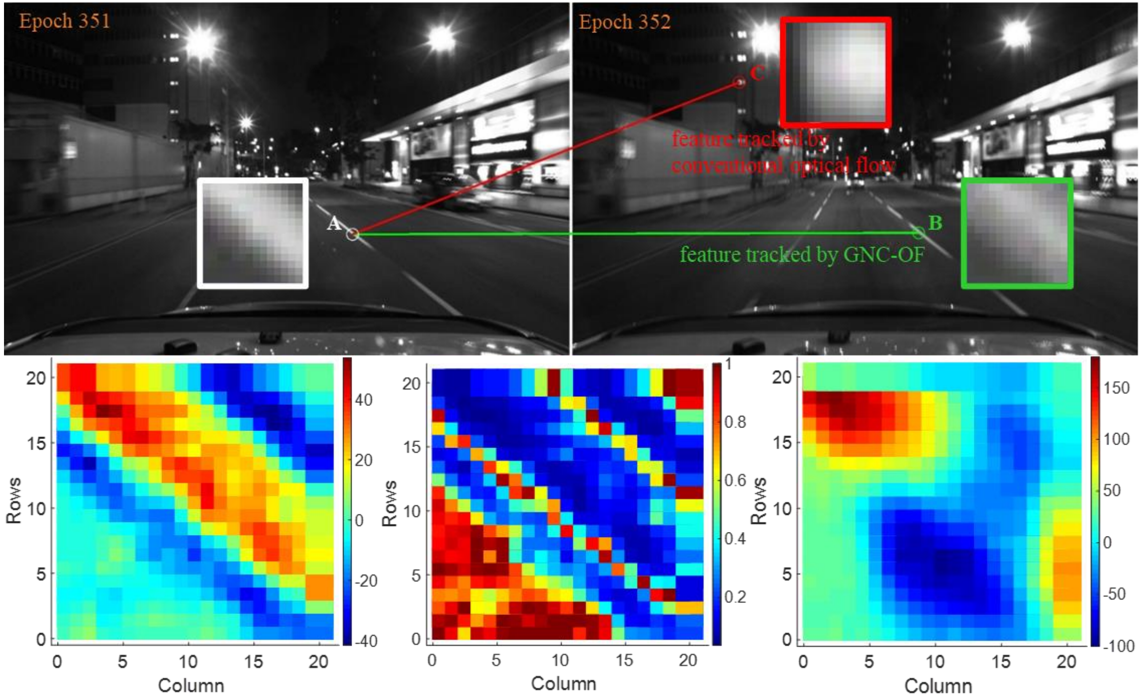




The residuals of visual reprojection in the u and v directions of conventional (VINS-Mono) and the proposed method (VINS-GNC-OF).

Experimental Results

Analysis of the residuals and weightings of the feature tracking of conventional optical flow from OpenCV and the feature tracking from GNC-OF at epochs 351 and 352.



(a) Residuals between feature A and B (tracked by GNC-OF)

(b) Weightings of each pixel of feature B (tracked by GNC-OF)

(c) Residuals between feature A and C (tracked by conventional optical flow)

Brief Summary

- Solved Problems: Detect the potential outliers caused by dynamic objects and remove, then increasing the features based on degeneration level.
- Limitations: The accumulated drift still exists.
- Current work: Investigating the global navigation satellite system (GNSS) to provide global positioning for VINS for intelligent vehicles.

Thank you for your attention

Q&A ☺