2D Ego-Motion with Yaw Estimation using Only mmWave Radars via Two-Way Weighted ICP

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Motivation

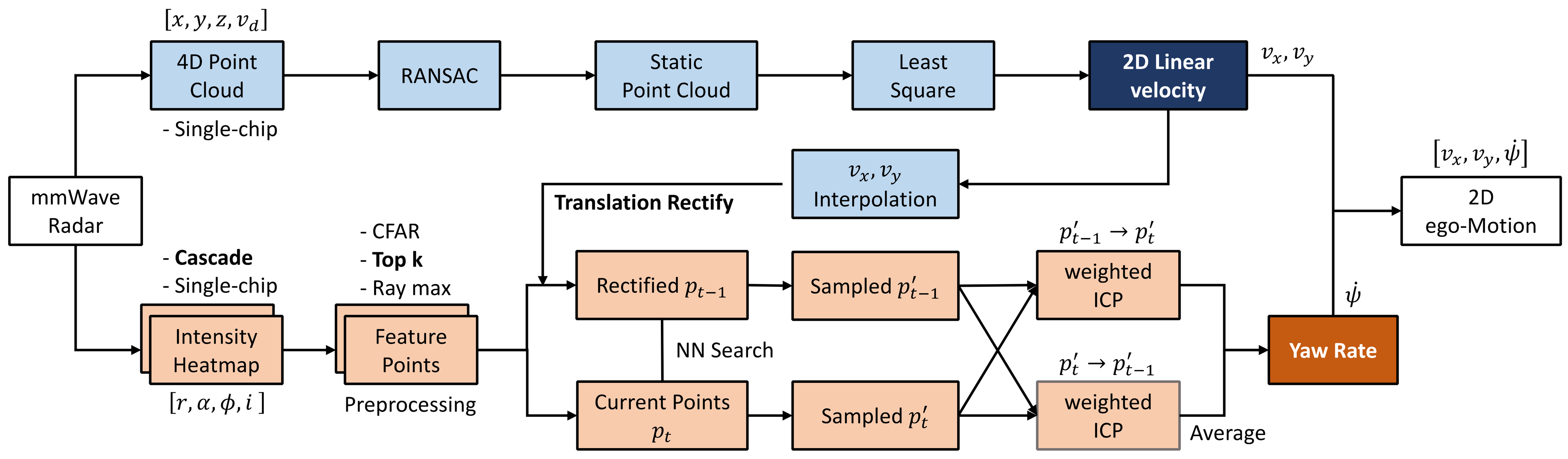
- Yaw rate estimation with mmWave radar is challenging
- Most radar odometry methods rely on integrating sensors or learning-based techniques
- Heatmap-based key-point matching is not attempted

Contributions

- Non-learning mmWave radar-only 2D ego-motion estimation without prior knowledge
- Heatmap Clutter matching via feature sampling and bidirectional mean ICP

Pipeline

- Exploit 2D linear velocity for translation rectification to enhance yaw rate estimation

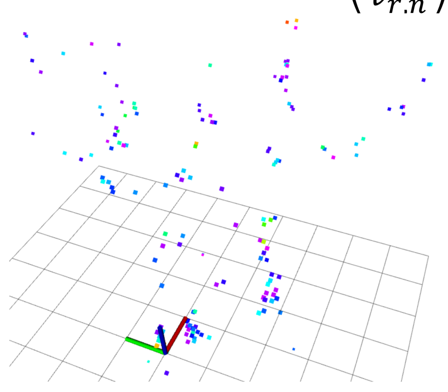


Methodology

- **2D Linear Velocity Estimation**

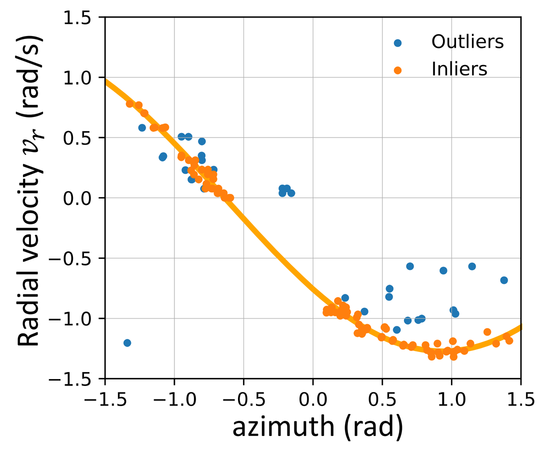
Estimate linear velocities in 4D point clouds from single-chip radar via RANSAC

$$\begin{pmatrix} v_{r,1} \\ \vdots \\ v_{r,n} \end{pmatrix} = \begin{pmatrix} \cos\theta_1 & \sin\theta_1 \\ \vdots & \vdots \\ \cos\theta_n & \sin\theta_n \end{pmatrix} \begin{pmatrix} v_x \\ v_y \end{pmatrix}, \quad v_r = \frac{\sqrt{x^2+y^2}}{r} v_d$$



4D Point Cloud
$[x, y, z, v_d]$

RANSAC →

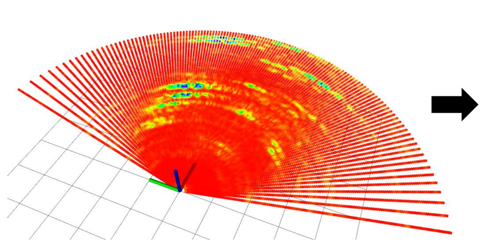


→ $\hat{v}_s = (v_x, v_y)$

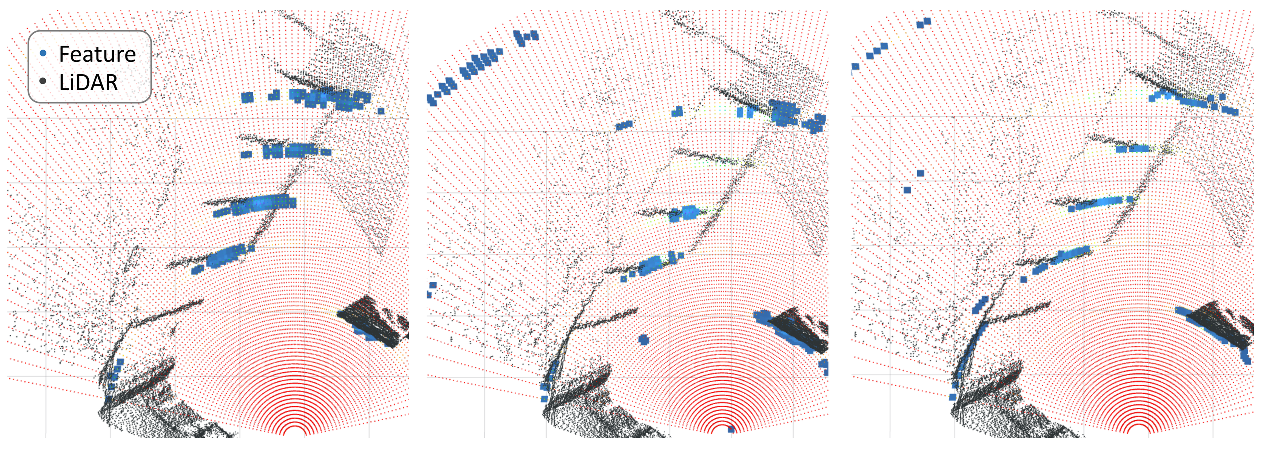
- **Heatmap Preprocessing**

Estimate yaw rate in intensity heatmap from cascade radar via feature point matching

3 Candidates: Top k , CFAR (Constant False Alarm Rate), Ray max



Intensity Heatmap
$[r, \alpha, \phi, i]$



Top k (# of points : 200) | CFAR (# of points : varies) | Ray max (# of points : 128)

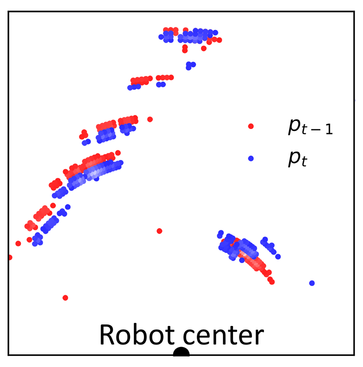
- **Time Synchronization for Translation Rectification**

Compensate the time difference between single-chip and cascade radars

Rectify translational error by estimated linear velocity from single-chip radar

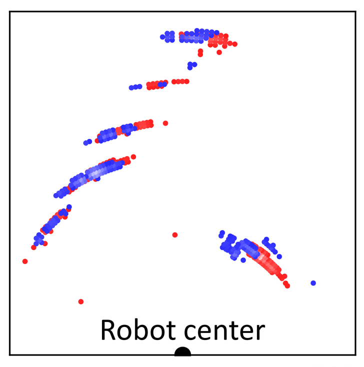
$$\hat{v}_c = \frac{\hat{v}_{s_t} - \hat{v}_{s_{t-1}}}{dt_s}\left(\frac{t_{c_t} + t_{c_{t-1}}}{2} - t_{s_{t-1}}\right) + \hat{v}_{s_{t-1}}$$

$$p_{t-1}^{rec} = p_{t-1} - \hat{v}_c dt_c$$



raw features p_{t-1}

Translation Rectification →



rectified features p_{t-1}^{rec}

- **Feature Sampling and Two-Way Weighted ICP**

Extract the key points from distance function to ensure the fast convergence

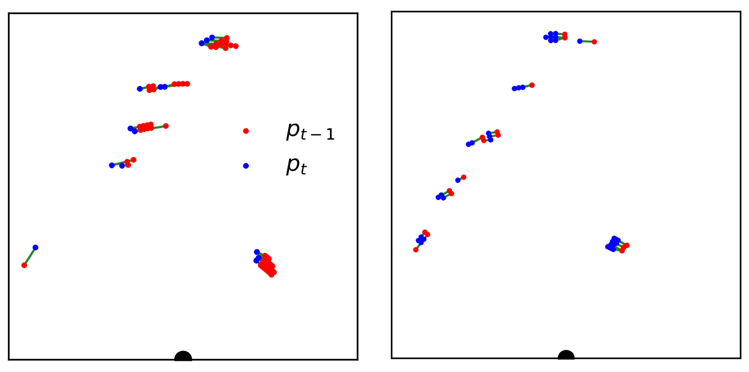
To assure robustness for clutter size, conduct bidirectional intensity weighted ICP (***wICP***)

Distance Function : $e_{ij} = \alpha(r_i - r_j)^2 + \beta(\theta_i - \theta_j)^2$

Feature Sampling: $p_{src} = \begin{cases} remove & \text{if } e_{min} > \epsilon_{max} \\ neglect & \text{if } e_{min} > \epsilon_{max} \text{ or out of ROI} \\ match & \text{else} \end{cases}$

wICP: $R^* = \arg\min_R \sum_i w_i \|y_i - Rx_i\|^2 = \arg\max_R \operatorname{tr}(R^T H)$

$$H = \sum_i w_i x_i y_i^T = UDV^T, \quad R^* = UV^T \in SO(2)$$



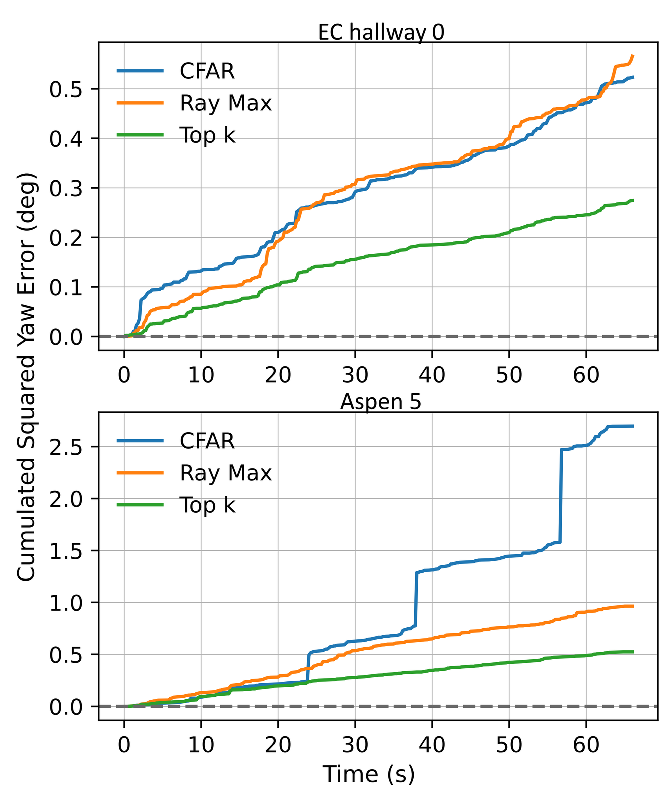
Previous -> Current Match pair | Current -> Previous Match pair

Mean of two-way weighted ICP (***mwICP***)

Results

- **Preprocessing Methods**

2 Sequences from ColoRadar[2] Dataset

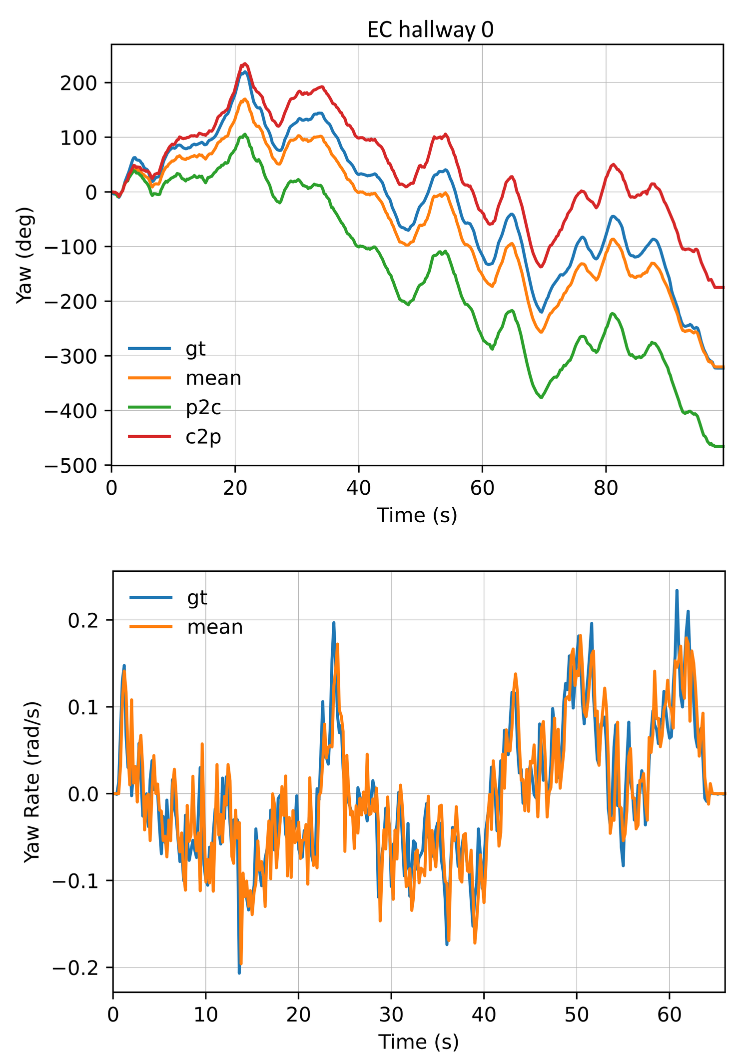


Dataset	CFAR	Ray max	Top k
EC Hallways 0	1.86	1.94	**1.35**
Aspen 5	4.66	3.09	**2.06**

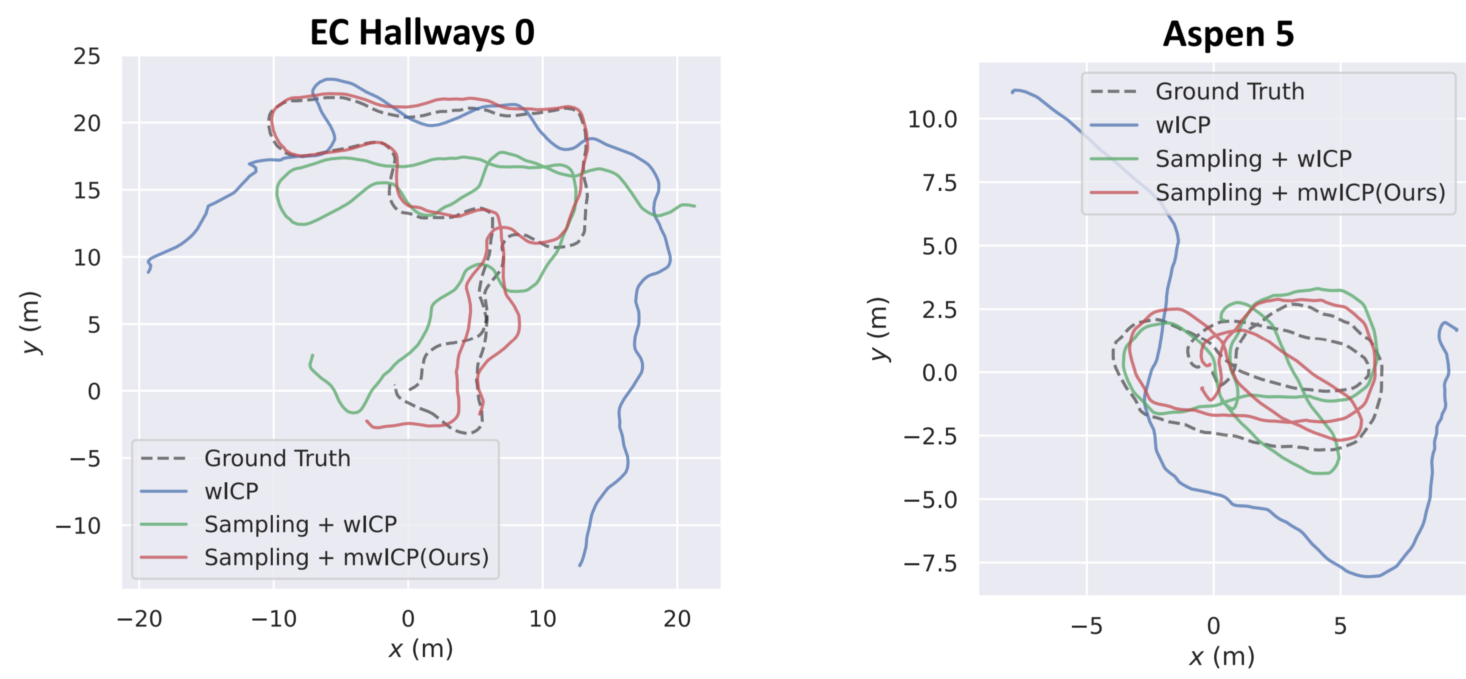
Table 1: Yaw RMSE [deg]

- **Yaw Rate Estimation**

Preprocessing with Top k + Sampling



- **2D Planar Odometry**

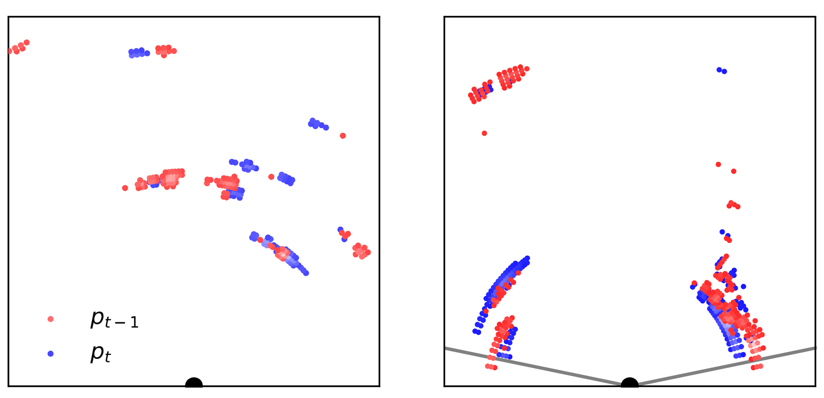


Dataset	wICP	Sampling + wICP	Sampling + mwICP
EC Hallways 0	0.0836	0.0124	**0.0086**
Aspen 5	0.0505	0.0077	**0.0066**

Table 2: Relative Pose Error [m]

- **Challenging Scenes**

1. Unstable features with no suitable target
   - Scene with numerous small objects
2. Curvature distortion of close points
   - Narrow hallway scene



1. Unstable Features | 2. Curvature Distortion

Conclusion & Future Works

- mmWave radar-only 2d ego-motion estimation
- Feature point registration via mean weighted ICP
- Cascade radar heatmap utilization to address the limitation of yaw rate estimation in mmWave radar
- Single chip radar-only to perform ego-motion estimation

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References
[1] Y. Zhou, L. Liu, H. Zhao, M. López-Benítez, L. Yu, and Y. Yue, "Towards deep radar perception for autonomous driving: Datasets, methods, and challenges," Sensors, vol. 22, no. 11, p. 4208, 2022.
[2] A. Kramer, K. Harlow, C. Williams, and C. Heckman, "Coloradar: The direct 3d millimeter wave radar dataset," *The International Journal of Robotics Research*, vol. 41, no. 4, pp. 351–360, 2022.