DELO: Deep Evidential LiDAR Odometry using Partial Optimal Transport

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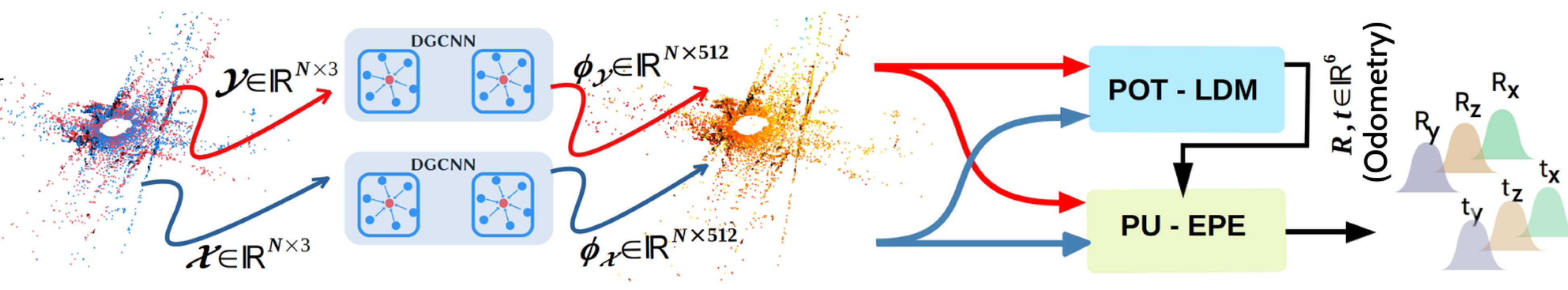
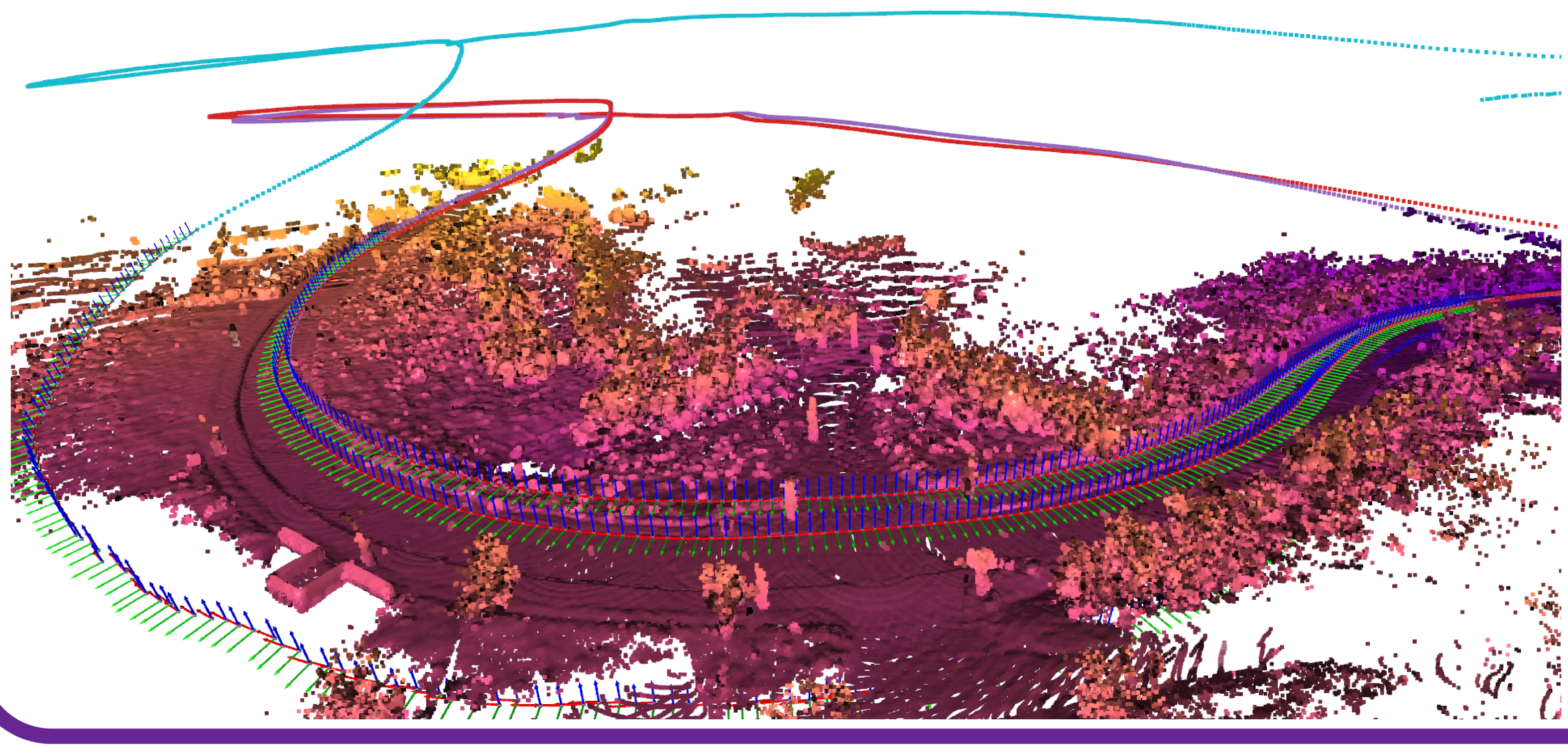
Real Problems for LiDAR Odometry

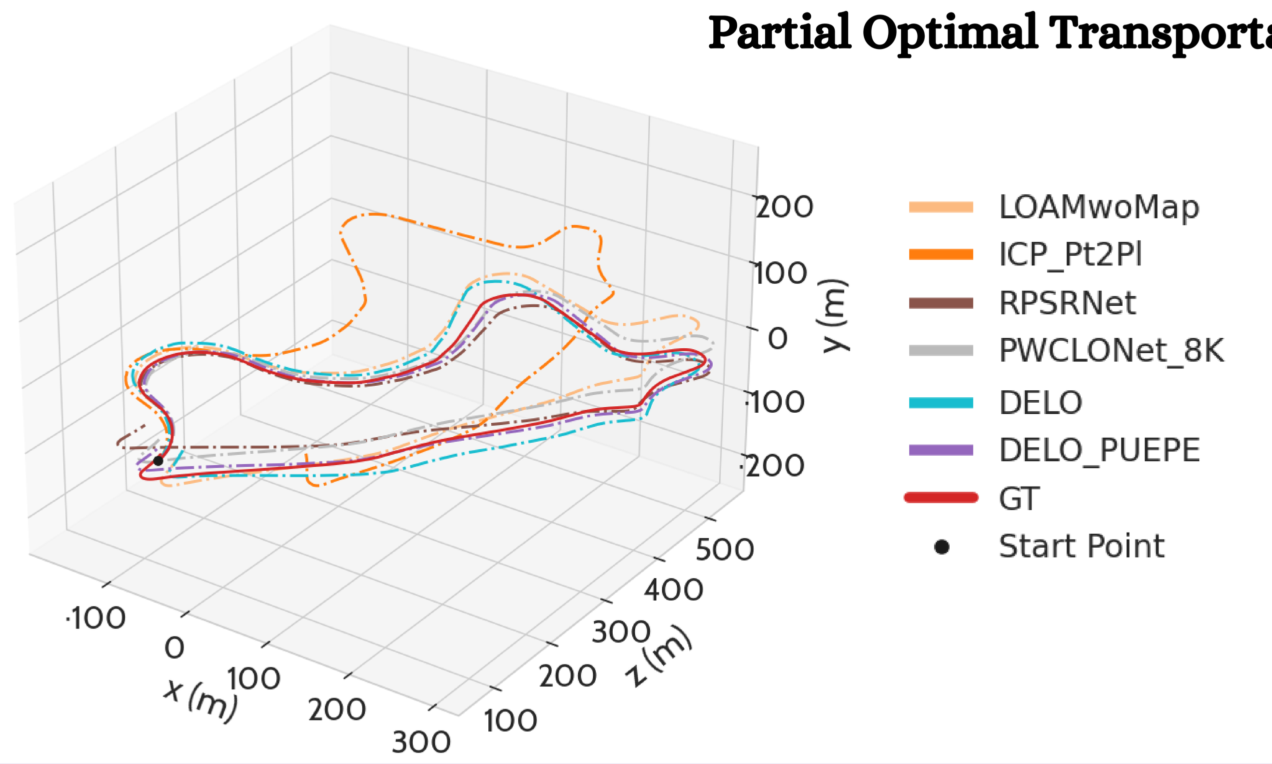
- **DELO** method proposes a multi-task learning framework:
  - **Accurate Relative Sensor Pose** estimation, i.e., LiDAR Odometry
  - **Predictive Uncertainty** estimation to flag LO-related anomalies
- **Differentiable Partial Optimal Transportation** of (i.e., source-to-target) "**sharp**" descriptor matching probabilities reduces **solution-multiplicity** issue in **"soft-assignment"** of correspondences
- **Predictive Uncertainty guided Evidential Pose Estimation (PU-EPE)** safeguards LO by classifying them as either (i) under-confident, (ii) confident, or (iii) overconfident pose estimates

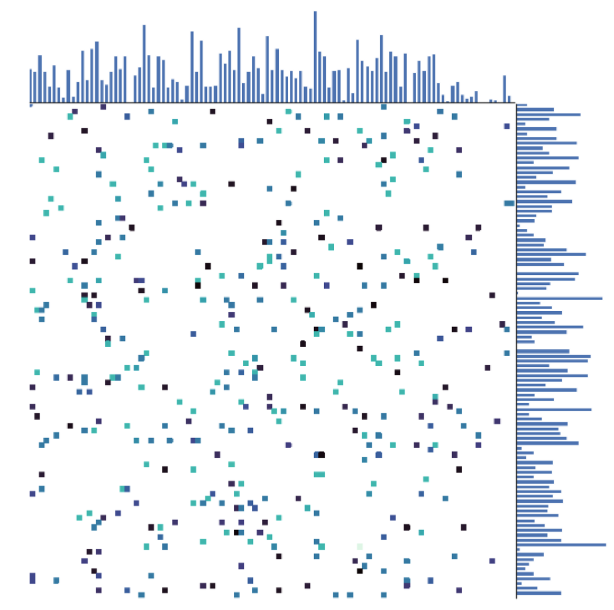


Relative Sensor Pose: $\mathbf{T} \in \mathrm{SE}(3) \triangleq \{(\boldsymbol{R}, \boldsymbol{t}) : \boldsymbol{R} \in \mathrm{SO}(3), \boldsymbol{t} \in \mathbb{R}^3\}$

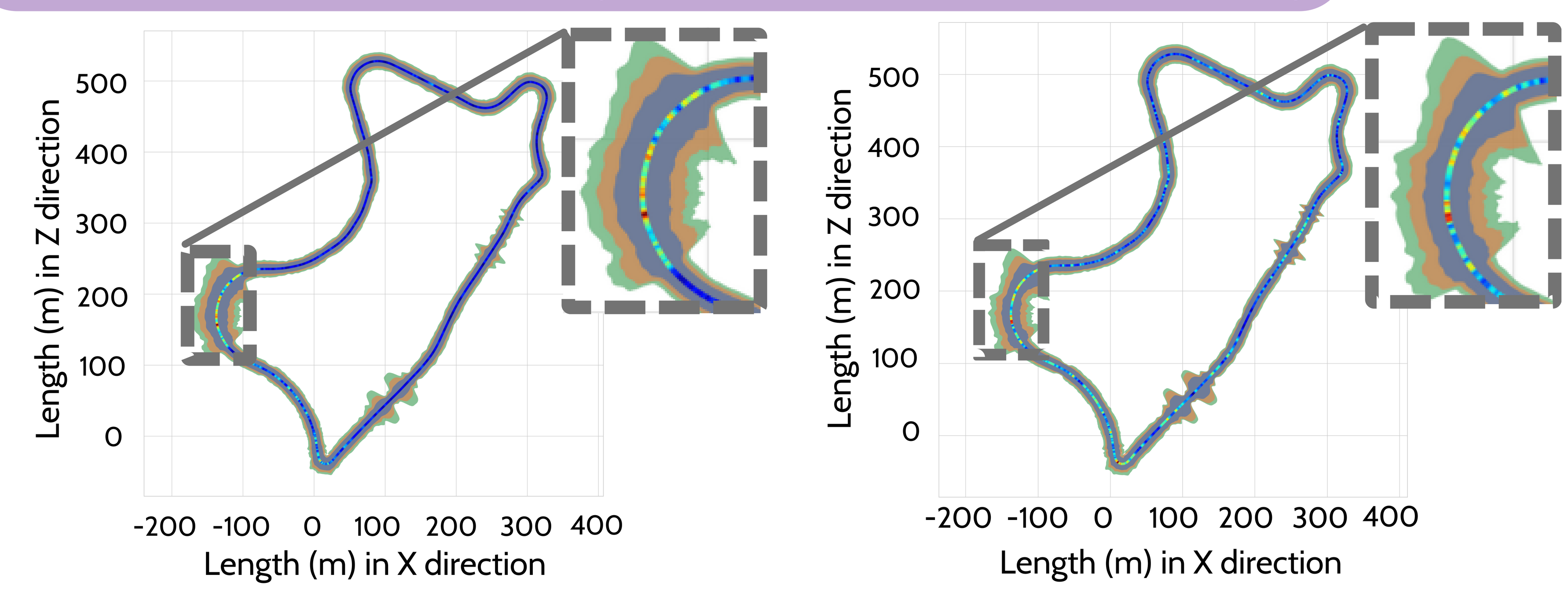


Soft-Assignments of correspondences are Sharpened using **Partial Optimal Transportation**





Predictive Uncertainty for Evidential Odometry



Network: $\boldsymbol{\phi}_\mathcal{X}$, $\boldsymbol{\phi}_\mathcal{Y}$, $\mathbf{T}$ → PU-EPE → $\gamma\in\mathbb{R}^6$, $\nu\in\mathbb{R}^6$, $\alpha\in\mathbb{R}^6$, $\beta\in\mathbb{R}^6$

Model Fit and Minimize evidence Error:

$$\int \underbrace{p(\mathbf{T}|\mu,\sigma^2)}_{\substack{\text{Likelihood}\\ \text{Normal Distr.}}}\ \underbrace{p(\mu,\sigma^2|\gamma,\alpha,\beta,\nu)}_{\substack{\text{Evidential Conjugate Prior}\\ \text{NormalInvGamma Distr.}}}$$

Model's Predictive Uncertainty (PU):

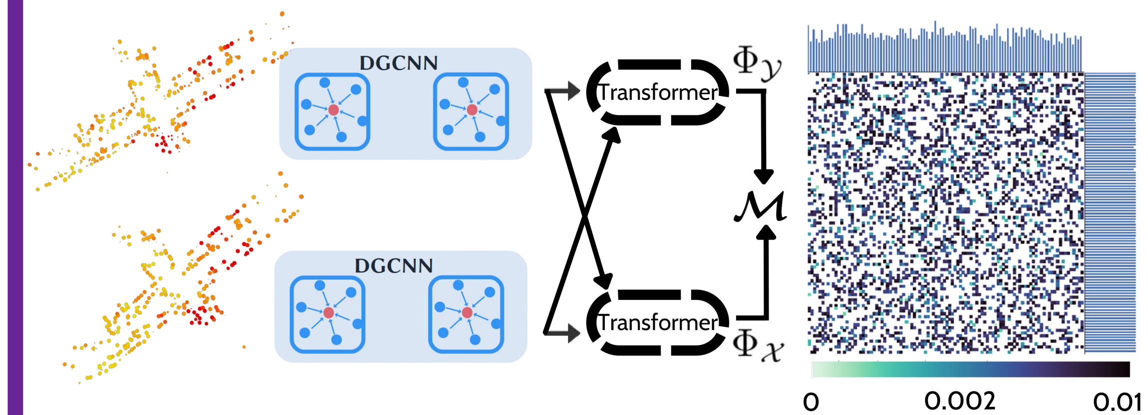
$$\mathrm{Var}[\mu] = \frac{\beta}{\nu(\alpha-1)}$$

Loss Functions:

$$\sum_{k=1}^{6}\left(\mathcal{L}^k_{NLL} = \frac{1}{2}\log\left(\frac{\pi}{\nu_k}\right) - \alpha_k\log(\Omega_k) + \left(\alpha_k+\frac{1}{2}\right)\log\left((\mathbf{T}_k-\gamma_k)^2\nu_k+\Omega_k\right) + log\left(\frac{\Gamma(\alpha_k)}{\Gamma(\alpha_k+1/2)}\right)\right.$$
$$\left. + \lambda_R\mathcal{L}^k_R = |\mathbf{T}_k - \gamma_k| * (2\alpha_k+\nu_k)\right)$$

Regularization Const. — Ground-truth Pose — Point Estimate $\mathbb{E}[\mu_k]$

Partial Optimal Transport

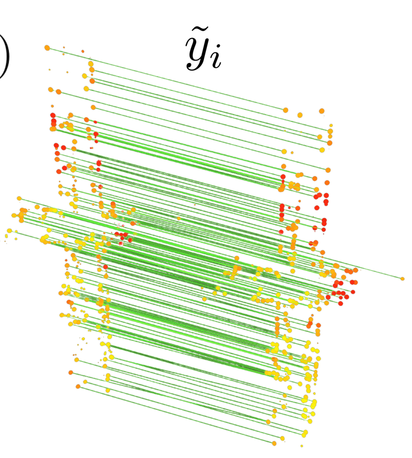


Step 1: $\Phi_\mathcal{Y} = \phi_\mathcal{Y} + \varphi(\phi_\mathcal{Y}, \phi_\mathcal{X}),\ \Phi_\mathcal{X} = \phi_\mathcal{X} + \varphi(\phi_\mathcal{X}, \phi_\mathcal{Y})$

Step 2: $C_{y_i} \leftarrow m(y_i, \mathcal{X}) = \mathtt{SoftMax}(\Phi_\mathcal{X}\Phi y_i^T)$

Step 3: Cost matrix C as the negative log-likelihood of the matching probabilities for every point $y_i \in \mathcal{Y}$ with all points in $\mathcal{X}$, and hence the matching cost:

$$\mathcal{M} = \arg\min_{\mathcal{M}} \langle \mathcal{M}, C\rangle_F + \lambda_M \Omega(\mathcal{M})$$
$$\Omega(\mathcal{M}) = \sum_{i,j}\mathcal{M}_{i,j}\log(\mathcal{M}_{i,j})$$
$$\tilde{y}_i \leftarrow \frac{1}{\sum_{j=1}^{n}\mathcal{M}_{ij}}\sum_{j=1}^{N}\mathcal{M}_{ij}y_i$$



Loss Functions:

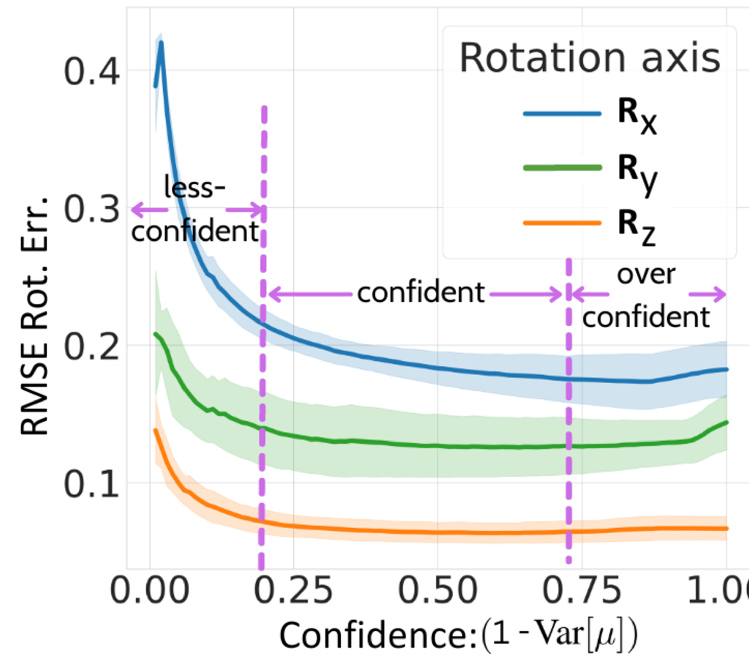
$$\mathcal{L}_{pose} = \frac{1}{N}\sum_{i=1}^{N}|\mathbf{T}y_i - \mathbf{T}y_i| + \mathcal{L}_{aux} = \frac{1}{N}\sum_{i=1}^{N}|\tilde{y}_i - \mathbf{T}y_i|$$

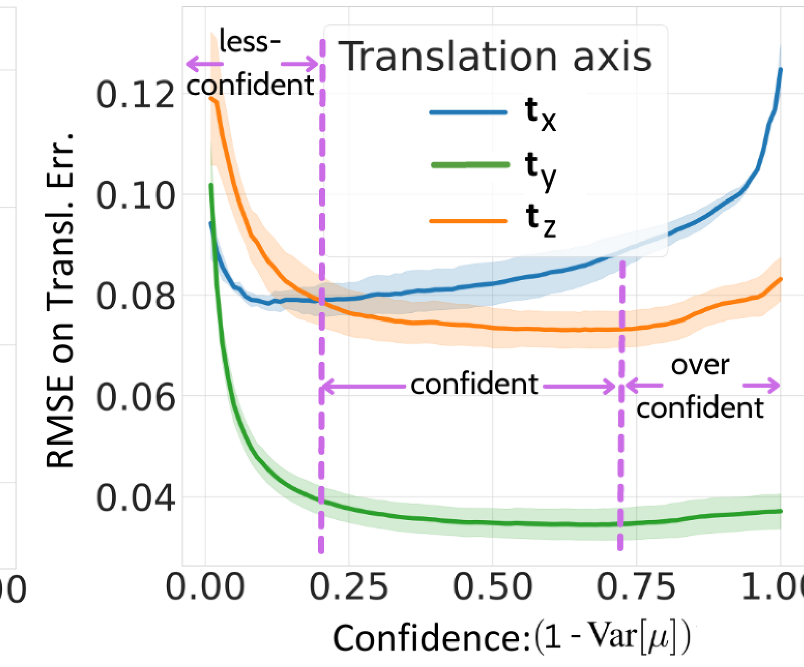
Experiments and Evaluation

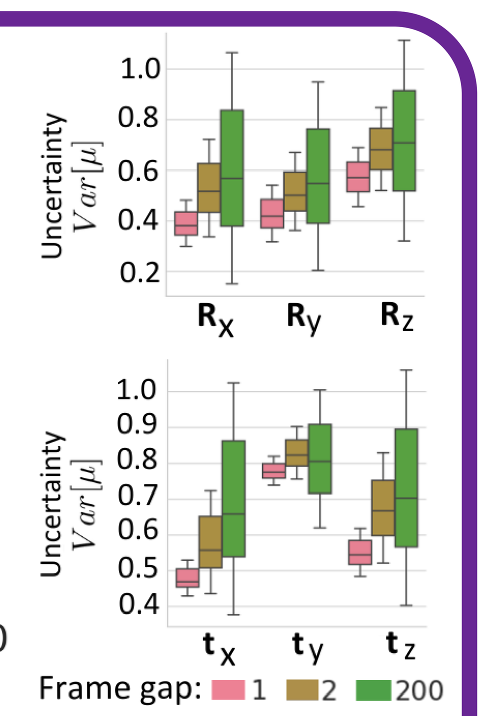
- If confidence score $1 - \mathrm{Var}[\mu]_{f\mapsto f+p}$ from **LO** prediction between two key-frames is bounded by the predefined thresholds θ_{min} and θ_{max}, the key frames are rejected for further pose-graph optimization (suggesting '**confident**' estimate):

$$\theta_{min} \leq 1 - \mathrm{Var}[\mu]_{f\mapsto f+p} \leq \theta_{max}$$

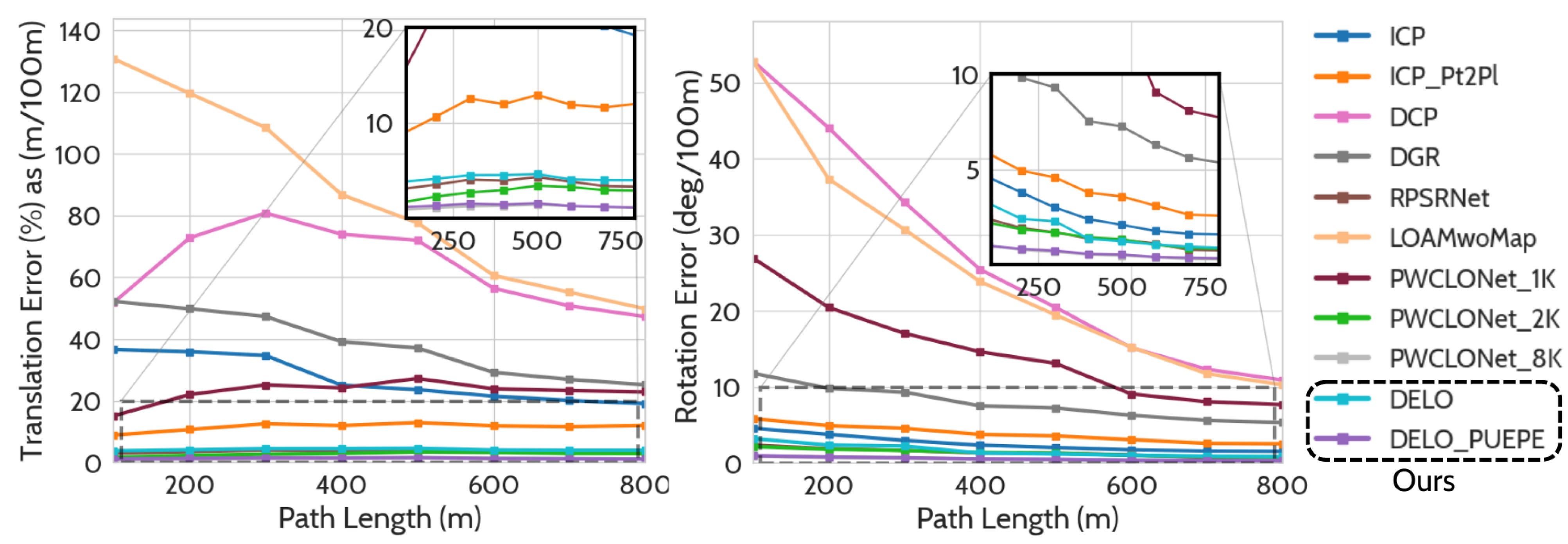
Upper bound for **Under-confident** estimates — Lower bound for **Over-confident** estimates







- SotA LiDAR data registration methods (e.g., DCP, DGR, RPSRNet) are not necessarily suitable for Odometry task
- Our **"Uncertainty guided" DELO + PUEPE** method is resistant to Out-of-order distribution (OOD) of relative sensor poses
- DELO-PUEPE outperforms PWCLONet
- Equivariant Nature of Pose Uncertainty estimator w.r.t Relative sensor Pose Error, i.e.,



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