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VisionNav Robotics

香港中文大學 The Chinese University of Hong Kong

# Visual-Odometric Localization and Mapping for Ground Vehicles Using SE(2)-XYZ Constraints

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## Objective and Motivation

- For ground vehicle SLAM, to estimate on-SE(2) ground vehicle poses without neglecting the out-of-SE(2) perturbation in real-world scenarios.

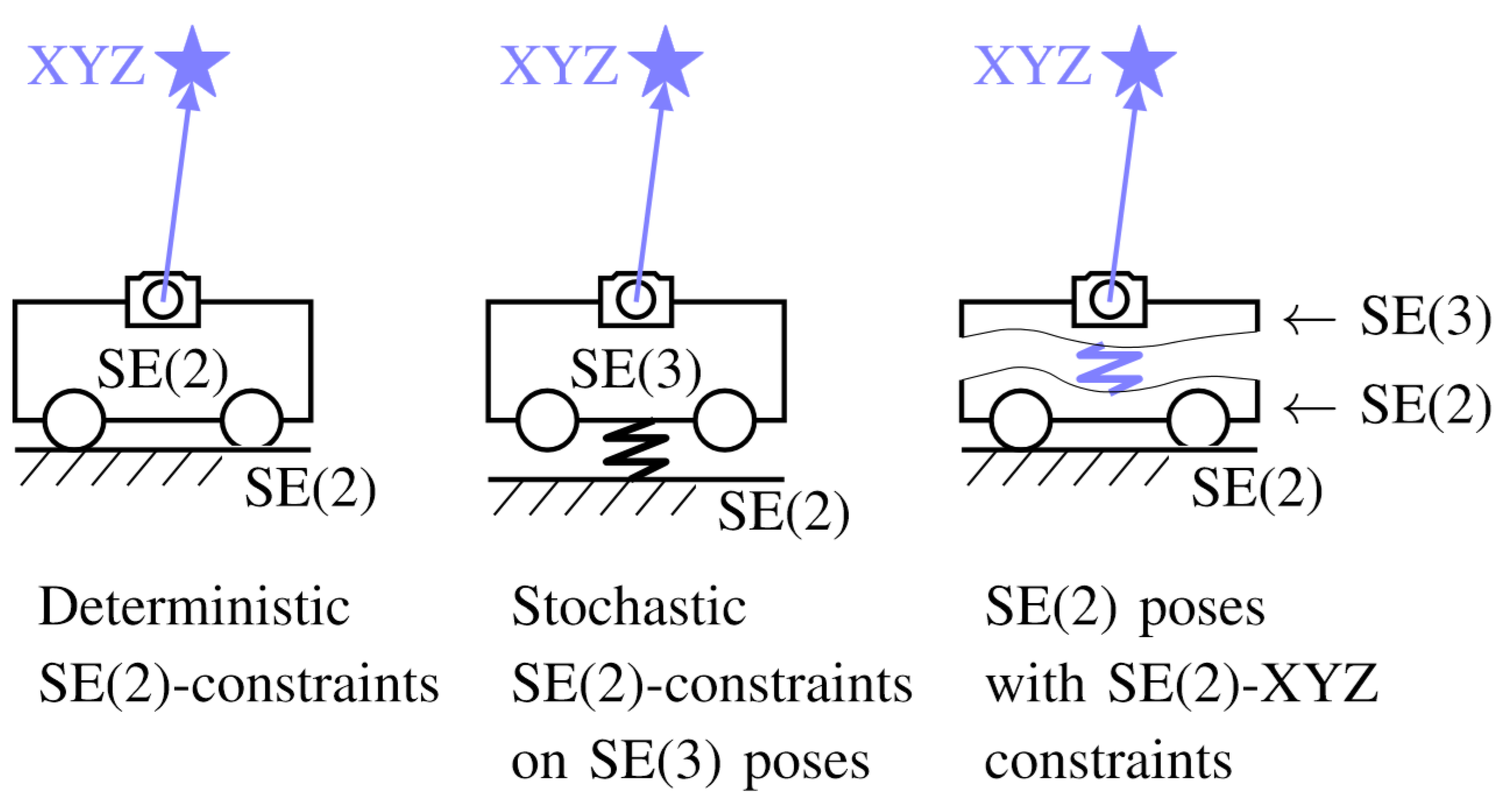



Fig 1. **(a)** Deterministic SE(2)-constraints are not accurate on rough terrains. **(b)** Stochastic SE(2)-constraints on SE(3) poses are accurate enough, but redundant. **(c)** SE(2)-XYZ constraints are compact and accurate

## Methodology

1. GRAPH OPTIMIZATION WITH

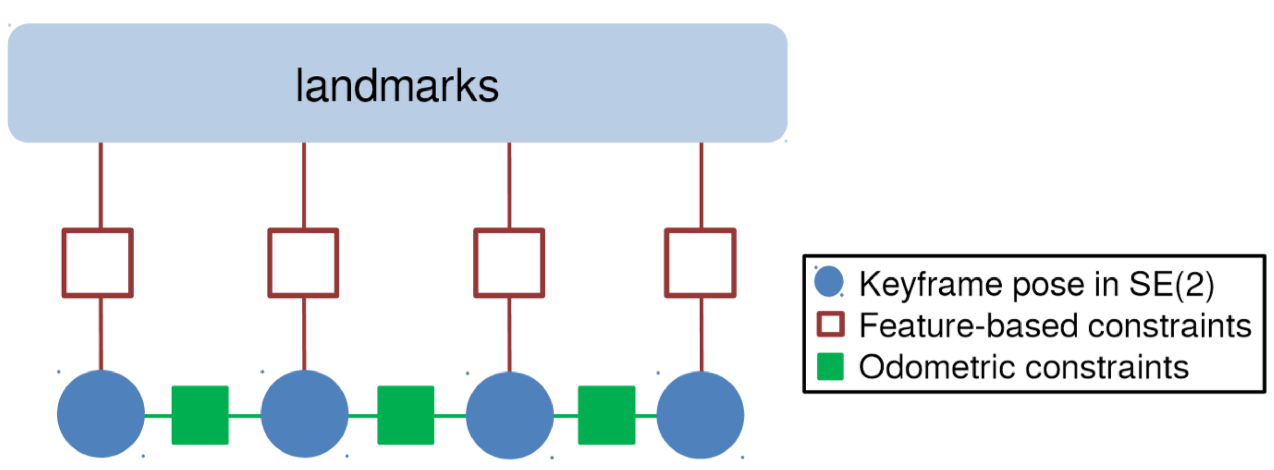



Fig 2. The graph structure for optimization.

1) **SE(2)-XYZ Constraints**

Consider the perturbed SE(2) poses on SE(3):

$$\mathbf{R}_i \leftarrow \mathrm{Exp}([\underbrace{\boldsymbol{\eta}_{\theta_{xy}}^T \;\; 0]^T)}_{\boldsymbol{\eta}_\theta}\mathbf{R}_i, \quad \mathbf{p}_i \leftarrow \mathbf{p}_i + \underbrace{[0 \; 0 \; \eta_z]^T}_{\boldsymbol{\eta}_z}.$$

Then the linearized measurement model for the constraint:

$$\begin{aligned}\mathbf{u}(\boldsymbol{\nu}_i, \mathbf{l}_\ell) &= \pi\left({}^C\mathbf{R}_B\mathbf{R}_i^T\mathrm{Exp}(-\boldsymbol{\eta}_\theta)(\mathbf{l}_\ell - \mathbf{p}_i - \boldsymbol{\eta}_z) + {}^C\mathbf{p}_B\right) \\ &+ \boldsymbol{\eta}_u \\ &\approx \pi({}_{C_i}\mathbf{l}_\ell) + \mathbf{J}^{\mathbf{u}}_{\boldsymbol{\eta}_\theta}\boldsymbol{\eta}_\theta + \mathbf{J}^{\mathbf{u}}_{\boldsymbol{\eta}_z}\boldsymbol{\eta}_z + \boldsymbol{\eta}_u\end{aligned}$$

2) **On-SE(2) Preintegrated Odometric Constraints**

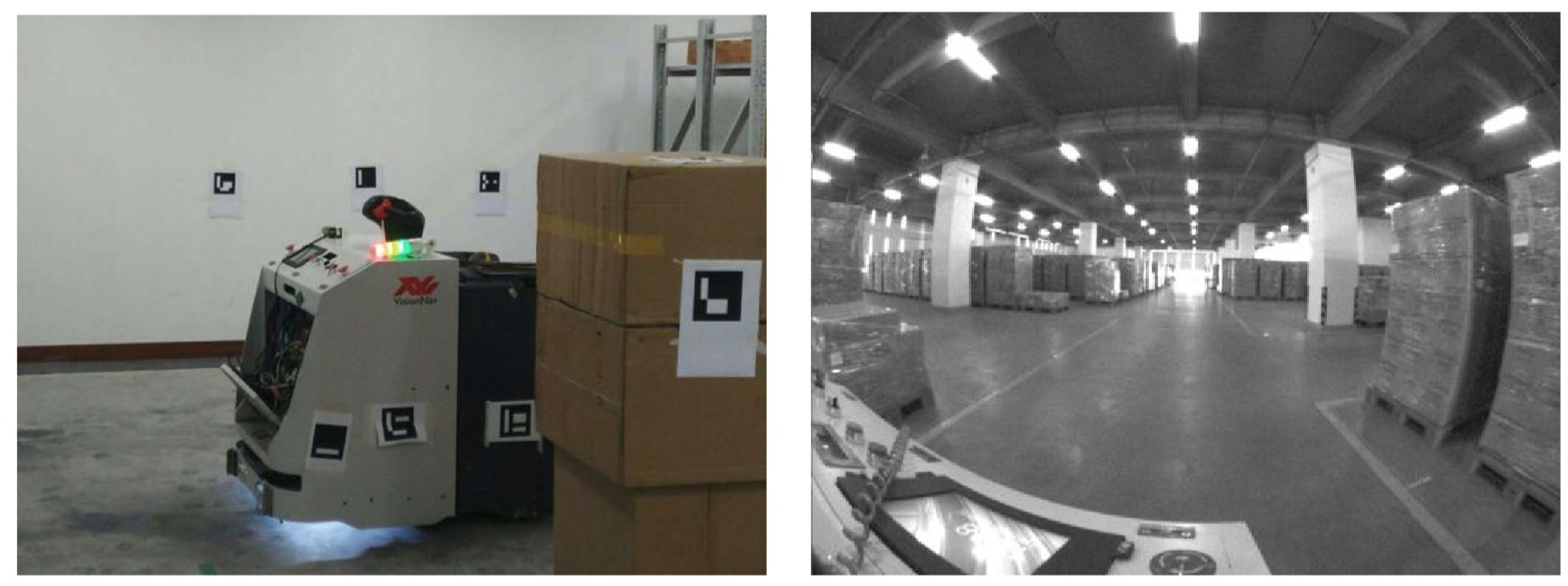
Similar to preintegration for VINS, but on SE(2):

$${}^i\phi_j = \sum_{k=i}^{j-1}(\tilde{\phi}_k - \eta_{\phi k}) = \sum_{k=i}^{j-1}\tilde{\phi}_k - \sum_{k=i}^{j-1}\eta_{\phi k}$$

$${}_i^i\mathbf{r}_j \approx \sum_{k=i}^{j-1}\Phi({}^i\tilde{\phi}_k)\tilde{\mathbf{r}}_k - \sum_{k=i}^{j-1}\Phi({}^i\tilde{\phi}_k)(\boldsymbol{\eta}_{rk} + \delta^i\phi_k^{\times}\tilde{\mathbf{r}}_k)$$

2. PARALLEL TRACKING, MAPPING, LOOP CLOSING

## Results



(a) AGV for experiments. (b) *Dataset Warehouse* environment.

Fig 3. The AGV and one testing field, by VisionNav Robotics Ltd.

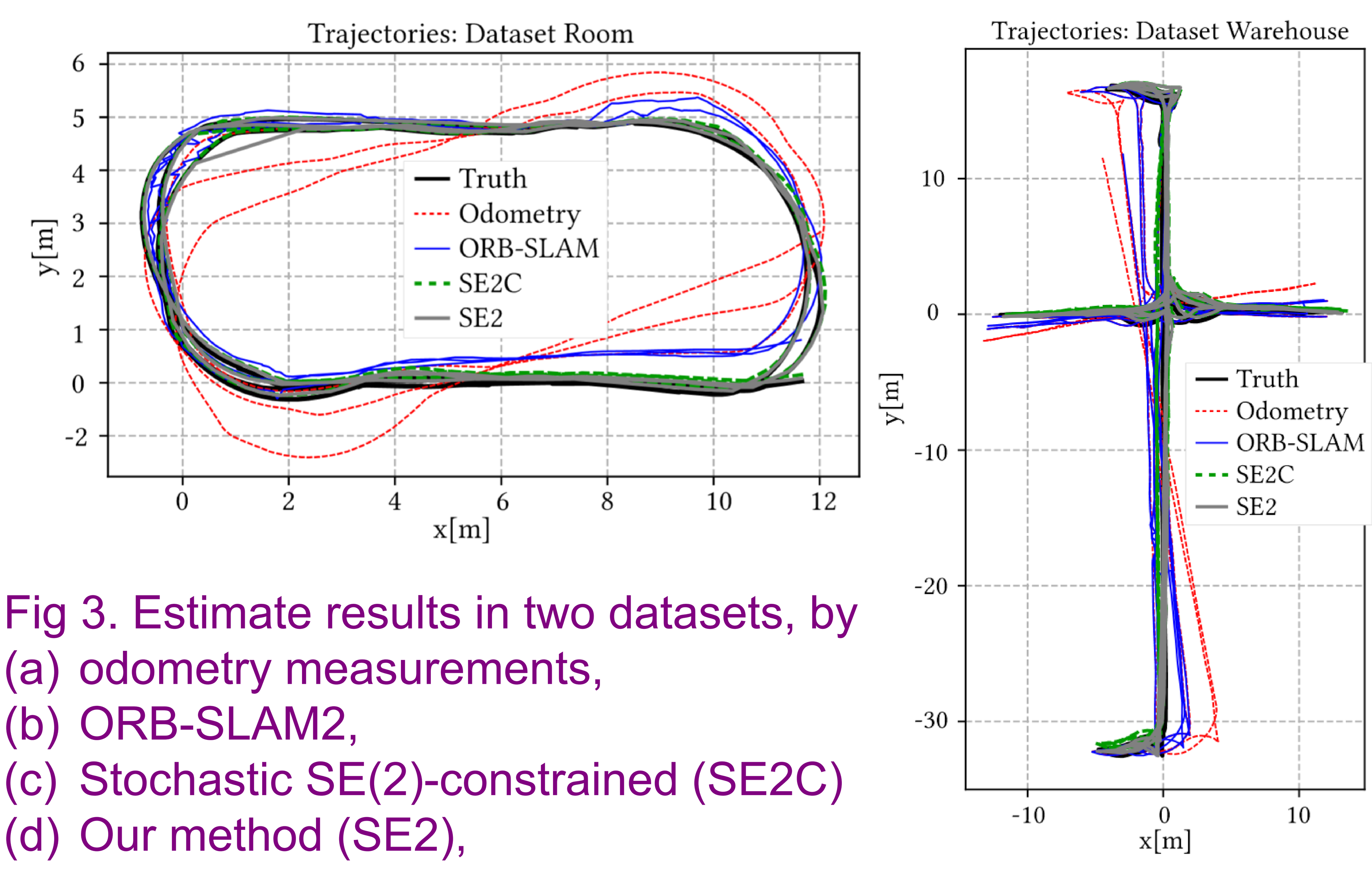



Fig 3. Estimate results in two datasets, by
(a) odometry measurements,
(b) ORB-SLAM2,
(c) Stochastic SE(2)-constrained (SE2C)
(d) Our method (SE2),
(e) the ground truth

TABLE I
ESTIMATION ERRORS STATISTICS (RMSE)

| | **Odom.** | **ORB-SLAM** | **SE2C** | **SE2** |
|---|---|---|---|---|
| DATASET ROOM | | | | |
| x err. (mm) | 541.24 | 135.33 | 62.44 | 61.106 |
| y err. (mm) | 1028.83 | 371.01 | 93.15 | 59.021 |
| $\phi$ err. (rad) | 0.24835 | 0.12809 | 0.01567 | 0.01181 |
| trans. err.(mm) | 1162.51 | 394.93 | 112.15 | 84.956 |
| accuracy* | 4.469% | 1.343% | 0.381% | 0.288% |
| DATASET WAREHOUSE | | | | |
| x err. (mm) | 1615.19 | 1038.66 | 304.22 | 171.129 |
| y err. (mm) | 460.90 | 507.13 | 393.87 | 279.766 |
| $\phi$ err. (rad) | 0.10062 | 0.17149 | 0.03924 | 0.04921 |
| trans. err.(mm) | 1679.67 | 1155.85 | 497.68 | 327.955 |
| accuracy | 1.142% | 0.787% | 0.339% | 0.223% |

*Accuracy is calculated by the translation error over the travel distance in *one loop*.

## More Info

- Open source !
  github.com/izhengfan/se2lam