Semantic Grid Map based LiDAR Localization in Highly Dynamic Urban Scenarios

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Planning, Perception and Navigation for Intelligent Vehicles

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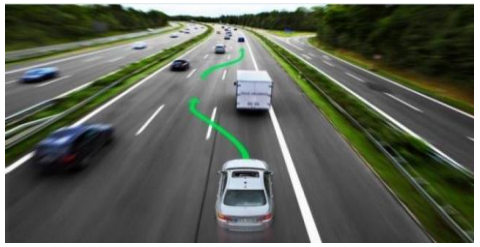
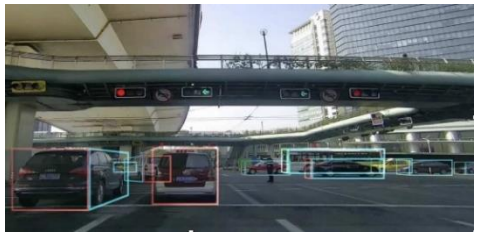
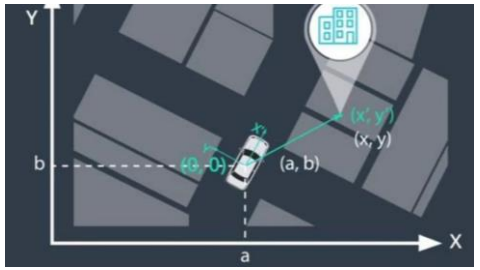
Introduction

Key tech. of autonomous driving

- Localization
- Planning
- Perception
- Navigation
- Control





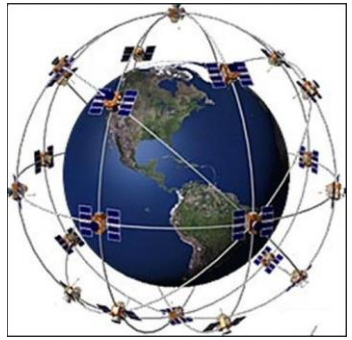


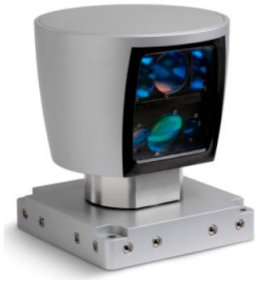
Introduction

Localization in AD

GNSS

Map-based pose estimation → Dynamic interferences





Signal denial
Multipath effect

Illuminance changes
Low reliability

Robust to illuminance
High reliability

Contents

Related work

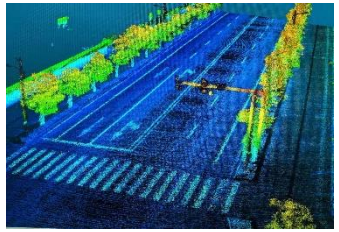
Environmental mapping

- GNSS-based
  - ✓ global consistency
  - • signal denial

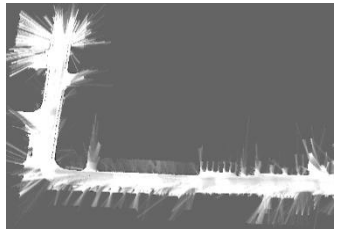
- SLAM-based
  - ✓ local consistency
  - • cumulative error

Map form

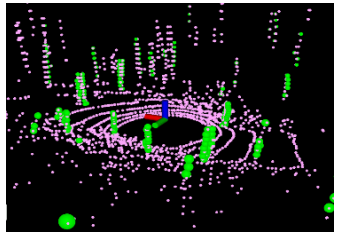
- Point cloud map
  - ✓ accuracy
  - • data size
  - • real-time performance

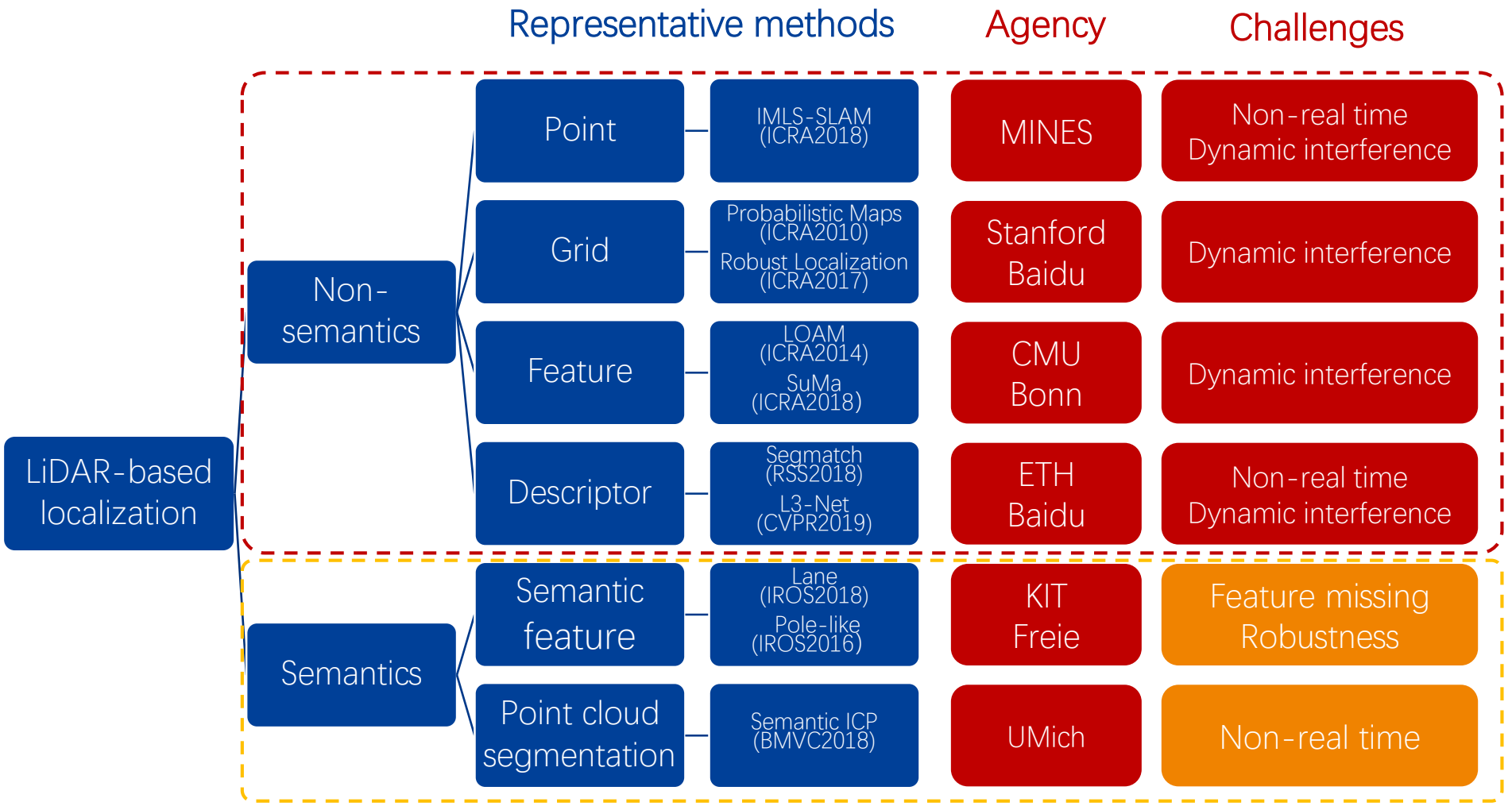


- 2D grid map
  - ✓ data size & speed
  - • information lost



- Feature map
  - ✓ accuracy & speed
  - • sensitive to the environment





Non-semantics: dynamic interference

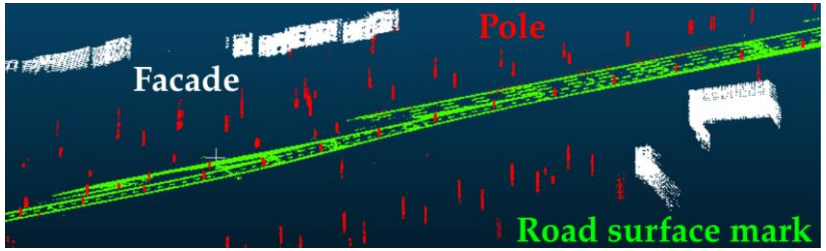
Semantics: difficult to find a balance between real-time and robustness

Multiple semantic features

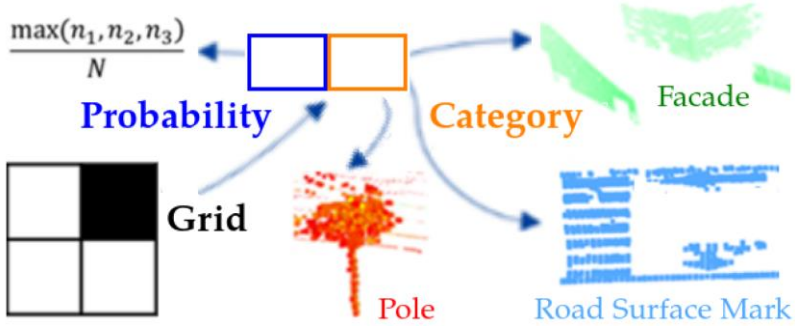
Contents

Semantic grid map

- Feature selection
  - Abundant in urban scenarios
  - Strongly imply static
  - Extractable from scan-level sparse point cloud
  - Sufficient pose constraints from multiple layers



- Semantic grid map
  - To speed up the calculation
  - Semantic category with a trust rate



Map structure	Size(MB/km)
Point cloud map	$\geq$ 1000
Semantic point cloud map	34
Grid map	5.3
Semantic grid map (Ours)	**1.1**

Contents

Localization

- On-line pose initialization
  - Large range search
  - Limited to the first several frames
  - Relatively low real-time requirements

  -> to keep as much map detail as possible, the SGM is in 3D formed by cubes

- Real-time trajectory tracking
  - Can inherit an accurate initial position from the previous frame
  - Every frame
  - Strict real-time requirements (typically 100ms)

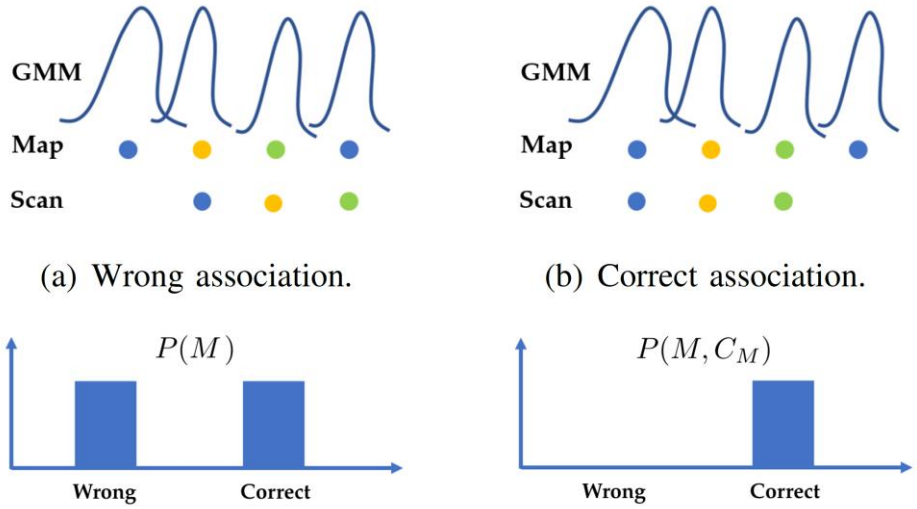
  -> to ensure the calculation speed, the SGM is in 2D formed by squares

Localization

- On-line pose initialization
  - Notation

    Map M Cubes $m_1, ..., m_J$

    Scan S Cubes $s_1, ..., s_K$



(a) Wrong association. (b) Correct association.

(c) Non-semantic probability. (d) Semantic probability.

$$P(m_j, C_{m_j}) = w\frac{1}{J} + (1-w)\sum_{k=1}^{K} P(C_{m_j}|m_j, s_k)P(m_j|s_k)P(s_k)$$

$P(C_{m_j}|m_j, s_k)$ → Semantic Category

$P(m_j|s_k)P(s_k)$ → GMM

$$= \frac{1}{2\pi|\Sigma_k|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(m_j - s_k)^T \Sigma_i^{-1}(m_j - s_k)\right)$$

$$= \begin{cases} \frac{\max(n_p, n_f, n_r)}{N} & C_{m_j} = C_{s_k} \\ 0 & C_{m_j} \neq C_{s_k} \end{cases}$$

$$T^* = \arg\max_T P(M, C_M) = \prod_{j=1}^{J} P(m_j, C_{m_j})$$

A. Myronenko and X. Song, "Point set registration: Coherent point drift," *IEEE transactions on pattern analysis and machine intelligence*, vol. 32, no. 12, pp. 2262–2275, 2010.

Real-time trajectory tracking

- Real-time trajectory tracking
  - Notation $A = \{a_{j,k}\}$ where $a_{j,k} = (m_j, s_k)$
  - Residual error $\varsigma = M - T \times S$

$$P(\varsigma, C, A|M, S) \propto \underbrace{P(\varsigma|A, M, S)}_{error} \underbrace{P(C|A, M, S)}_{label} \underbrace{P(A|M, S)}_{geometry}$$

$$= \prod \exp\left(\frac{-\|m_j - Ts_k\|^2}{2}\right)$$

$$= \begin{cases} 1/k & knn \\ 0 & otherwise \end{cases}$$

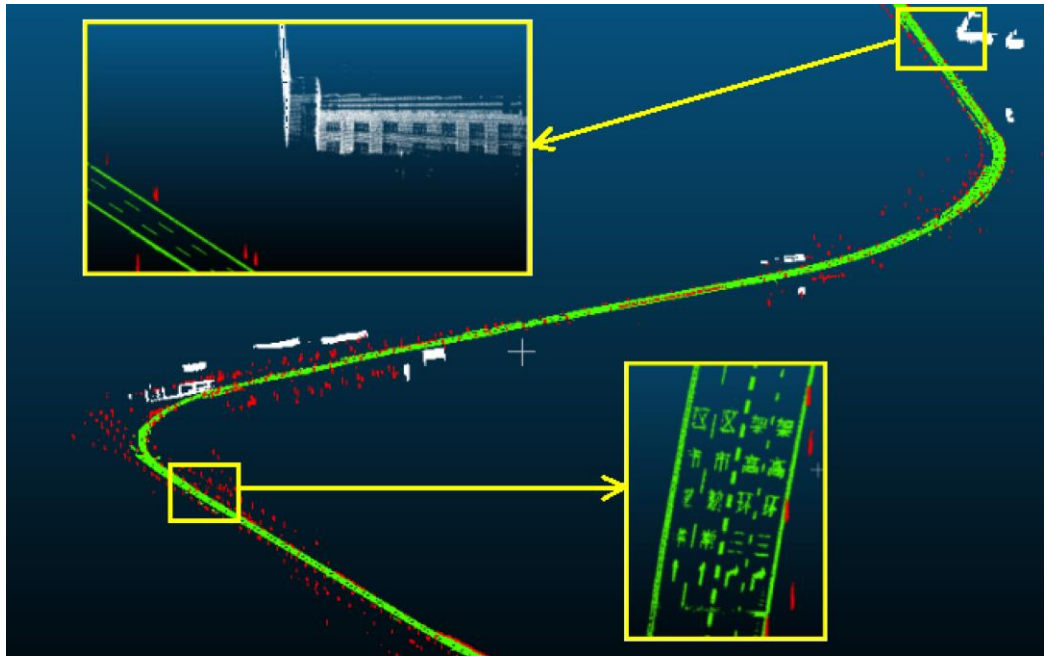
$$T^* = \arg\max_T P(\varsigma, C, A|M, S)$$

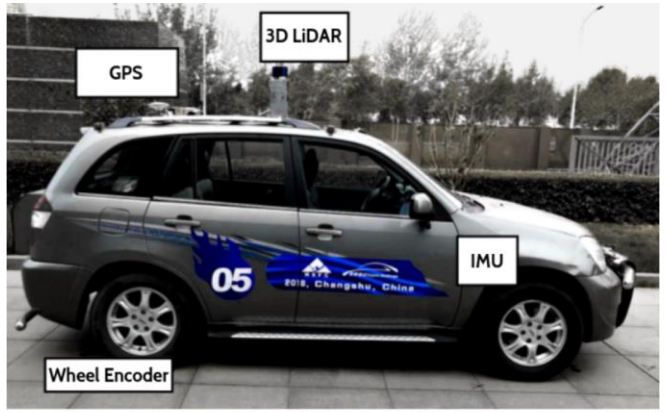
A. Myronenko and X. Song, "Point set registration: Coherent point drift," *IEEE transactions on pattern analysis and machine intelligence*, vol. 32, no. 12, pp. 2262–2275, 2010.

Contents

Experiment

- Processor
  - Intel i7-7567U @3.5GHz with 16GB memory
- Express road
  - 5.2km long

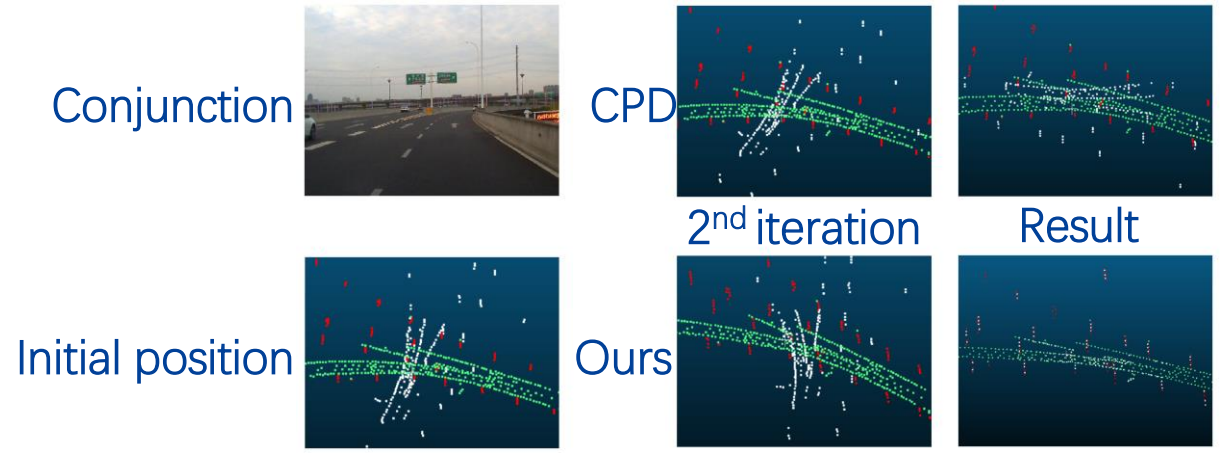




Experiment

- On-line pose initialization
  - $(0.2m)^3$ cube
  - horizontal offset uniform distribution in 50m circle
  - up to 90 degree offset
  - a special case

	Trans.(m)	30°	60°	90°
CPD	Mean	0.17	0.19	6.42
	Max	0.18	0.50	67.3
Our method	Mean	0.08	0.18	**0.13**
	Max	0.12	0.24	**0.30**
	Yaw.(°)	30°	60°	90°
CPD	Mean	0.18	0.19	3.83
	Max	0.20	0.48	6.80
Our method	Mean	0.13	0.13	**0.11**
	Max	0.16	0.16	**0.18**
	Calculation time (s)			90°
CPD	Mean			7.25
Our method	Mean			**3.23**



Experiment

- Real-time trajectory tracking
  - $(0.1\text{m})^2$ square

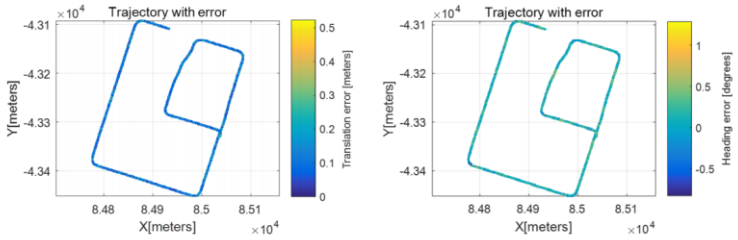
	Lat.(m)	Lon.(m)	Trans.(m)	Yaw.(°)
Semantic ICP	0.20	0.24	0.31	**0.20**
Grid Localization	0.11	≥ 2	≥ 2	≥ 2
Poles	0.37	0.33	0.55	1.86
Road marks	0.10	≥ 2	≥ 2	0.37
Facades	0.09	-	-	0.54
Our method	**0.08**	**0.12**	**0.16**	0.27

Method	Mean operation time(ms)
Semantic ICP	150.40
Grid Localization	44.03
Poles	15.14
Road marks	16.34
Facades	14.08
Our method	23.41

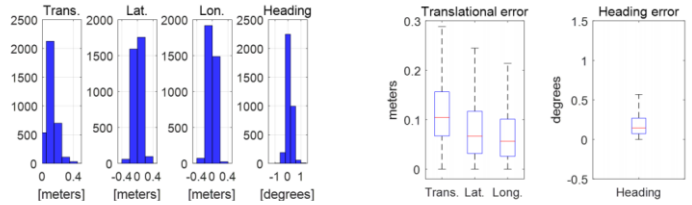
Experiment

- Processor
  - Intel i7-7567U @3.5GHz with 16GB memory
- Factory
  - 1.5km long

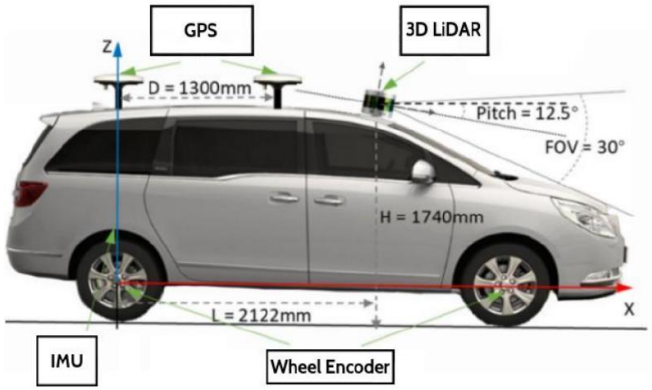
	Trans.(m)	Lat.(m)	Lon.(m)	Yaw.(°)
Express road	0.14	0.06	0.11	0.21
Factory	0.12	0.07	0.08	0.19



(a) Translation error. (b) Heading error.



(c) Error histogram. (d) Error boxplot.



Thank you for your attention!