三维点云处理技术
和深度学习在点云处理中的应用

深度学习在激光SLAM中的应用

索传哲

内容概要

深度学习与激光SLAM的结合点

Deep Lidar Odometry

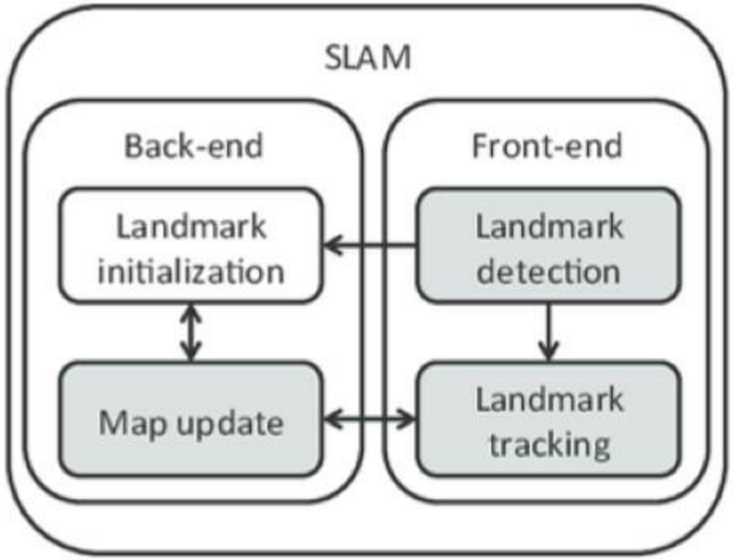
Deep Lidar Loop Closure Detection

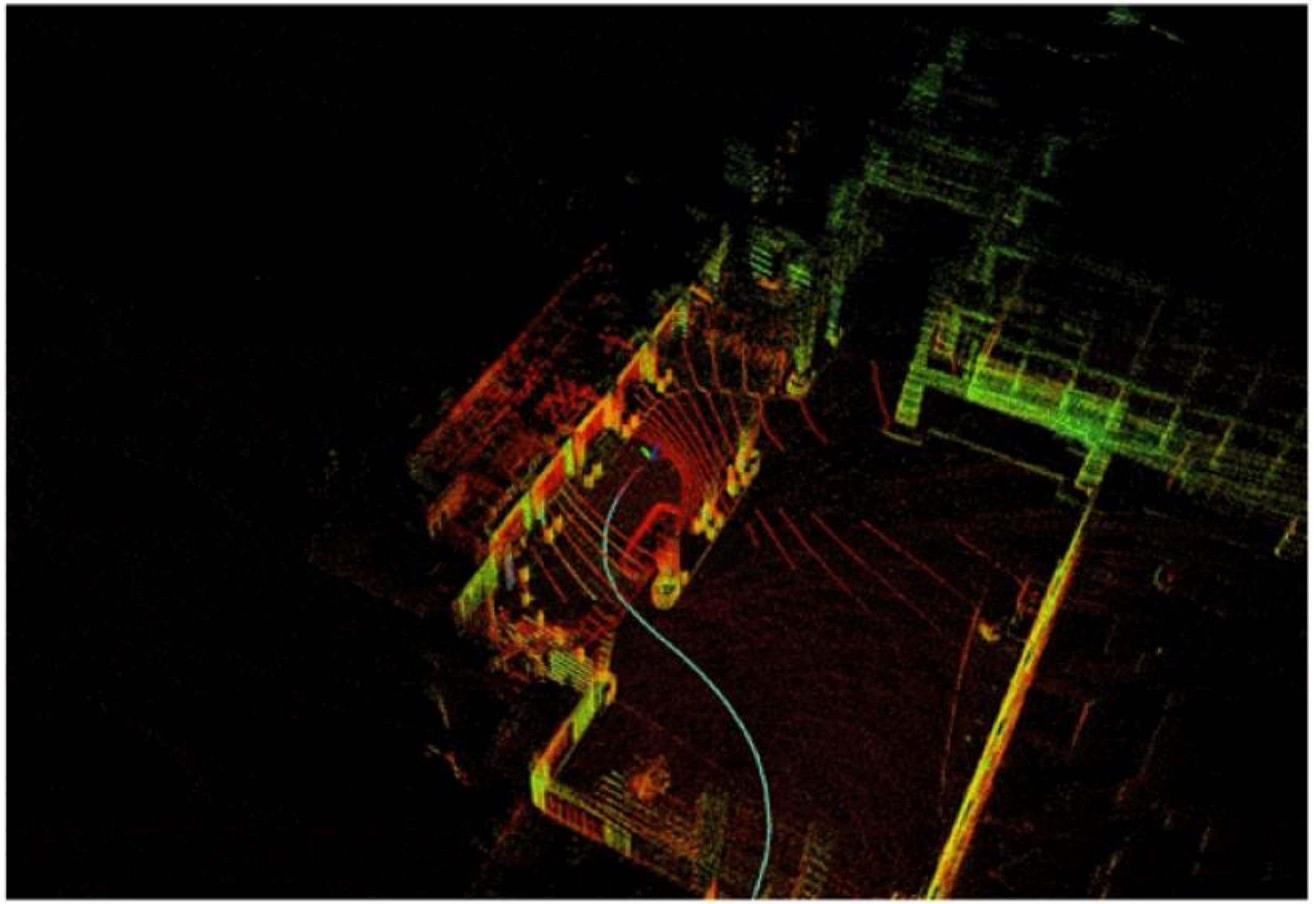
深度学习与激光SLAM的结合点

- Deep Learning in Lidar SLAM

✓ Lidar SLAM

- Front-end： Odometry
- Back-end： Optimization





深度学习与激光SLAM的结合点

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✓ Lidar SLAM

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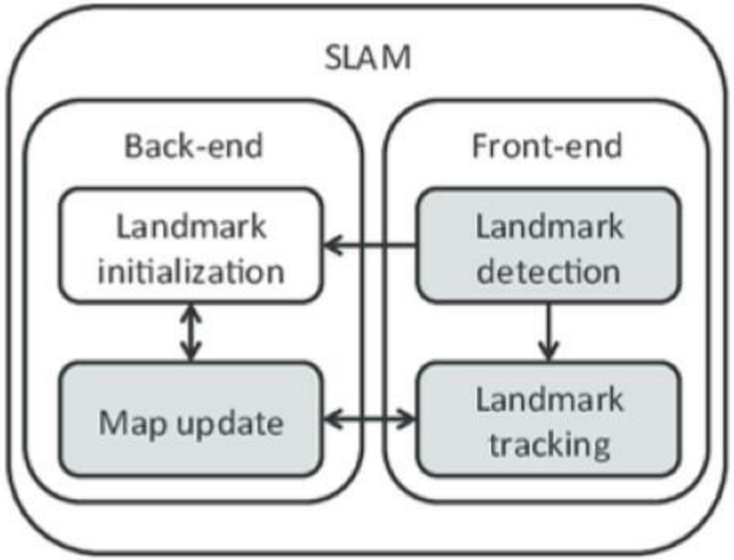
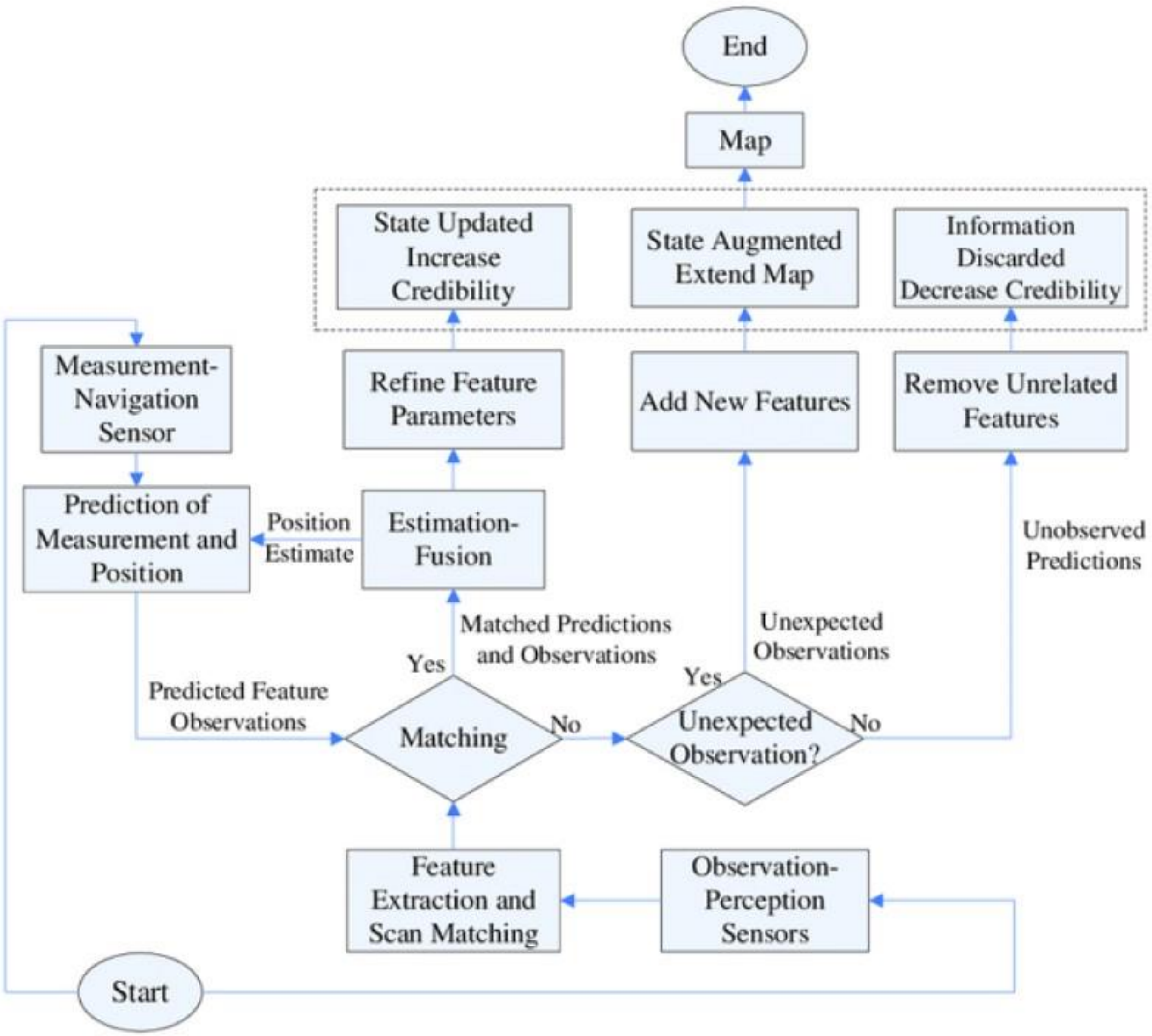
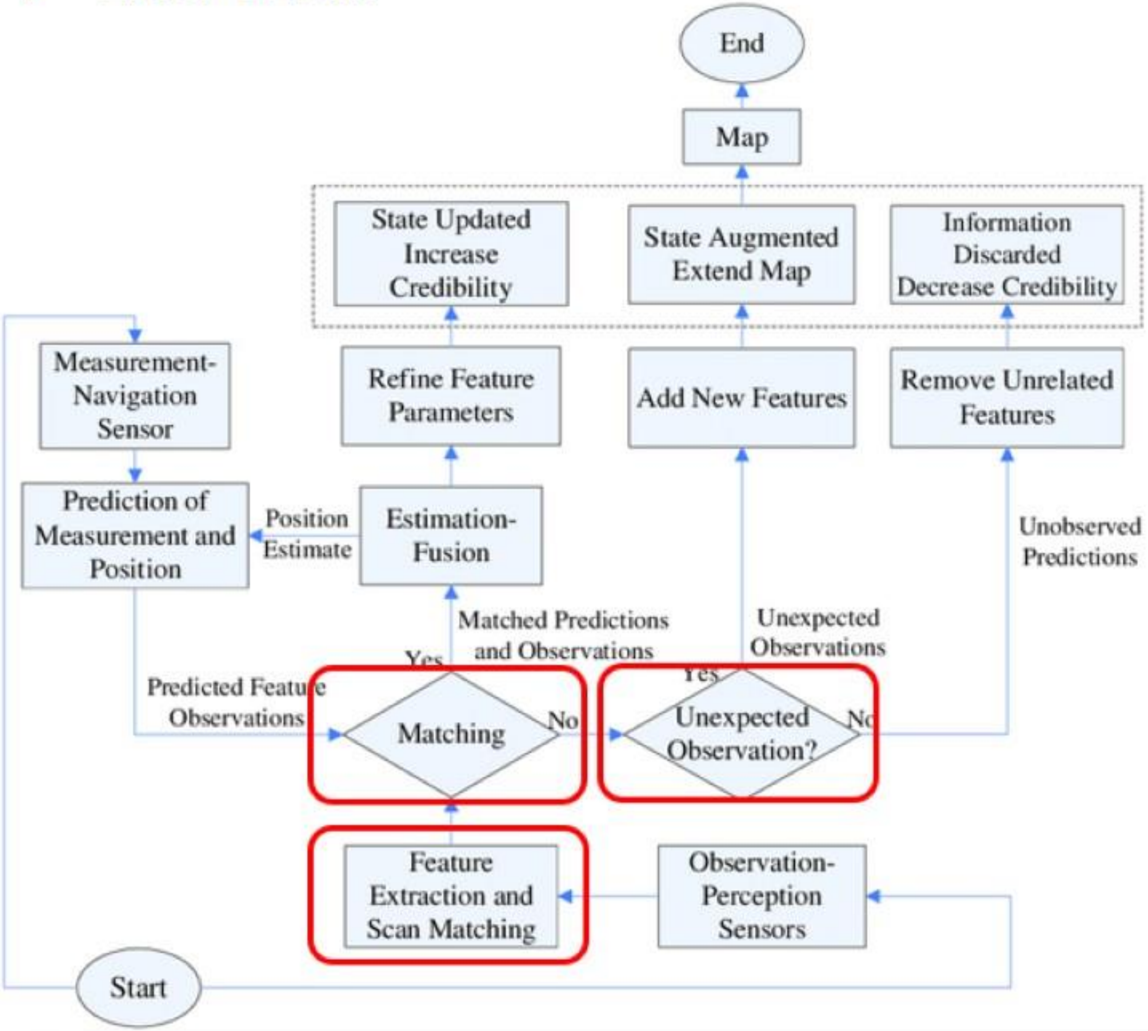




深度学习与激光SLAM的结合点

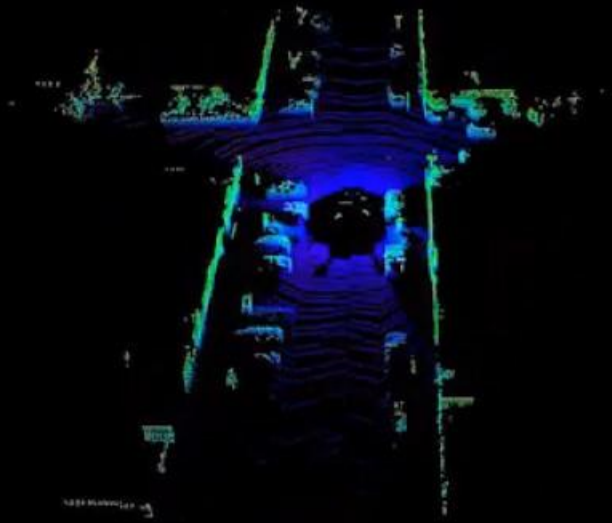
- Deep Learning in Lidar SLAM
  - ✓ Lidar SLAM



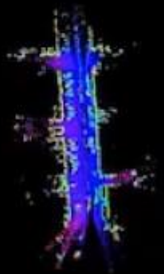
- Front-end： Odometry
  - KeyPoints Detection
  - Feture Extraction
  - Feature Association
  - Landmark Fileter

Evaluation on KITTI 00
(DeepLO-Uns)

Current point cloud



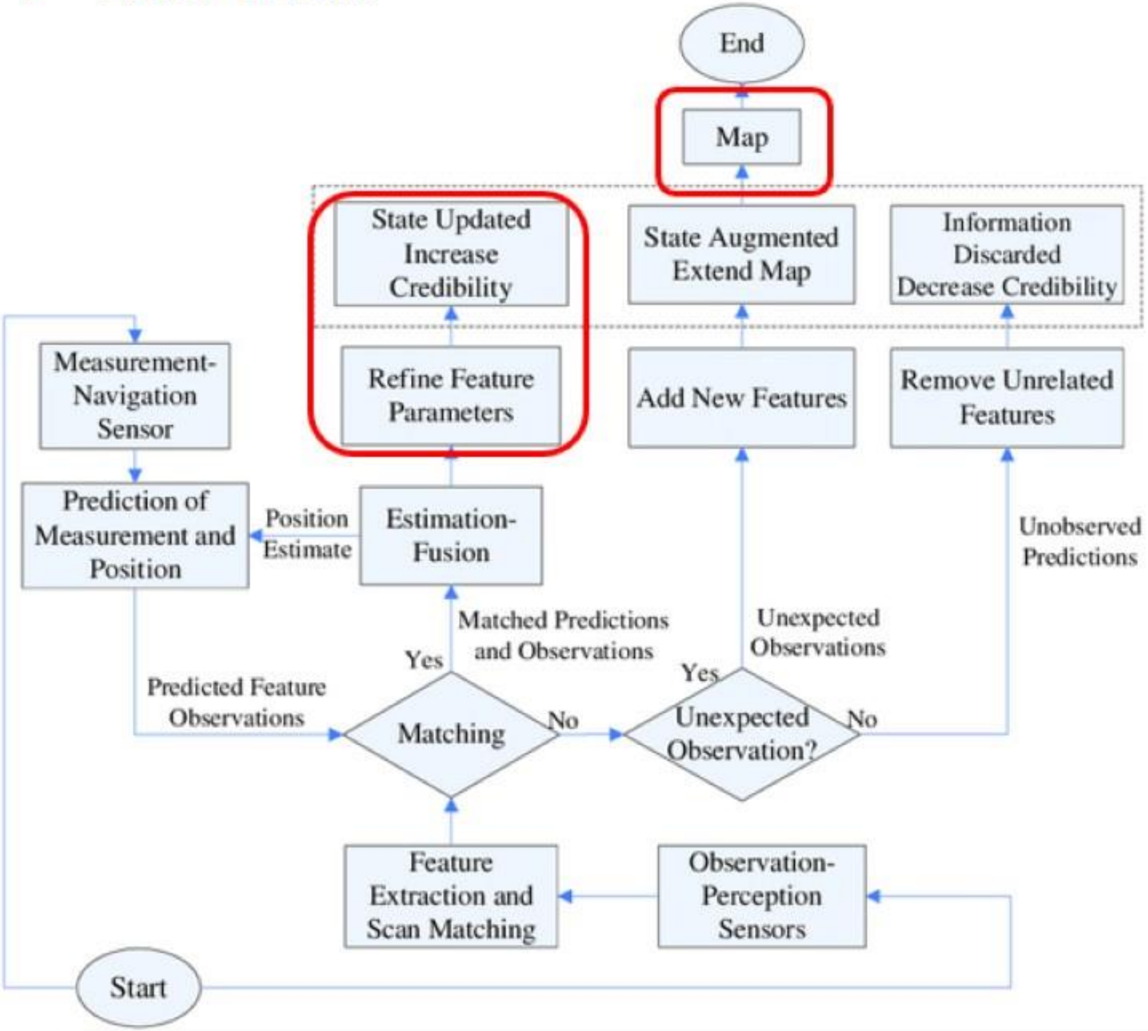
Current vertex map
(represented as range image for visualization)



Global trajectory with point clouds

深度学习与激光SLAM的结合点

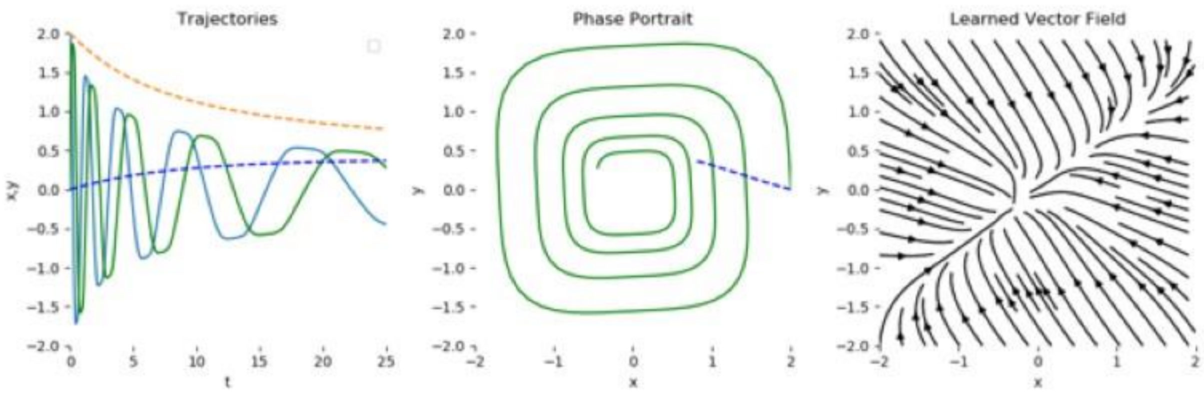
- Deep Learning in Lidar SLAM
  - ✓ Lidar SLAM



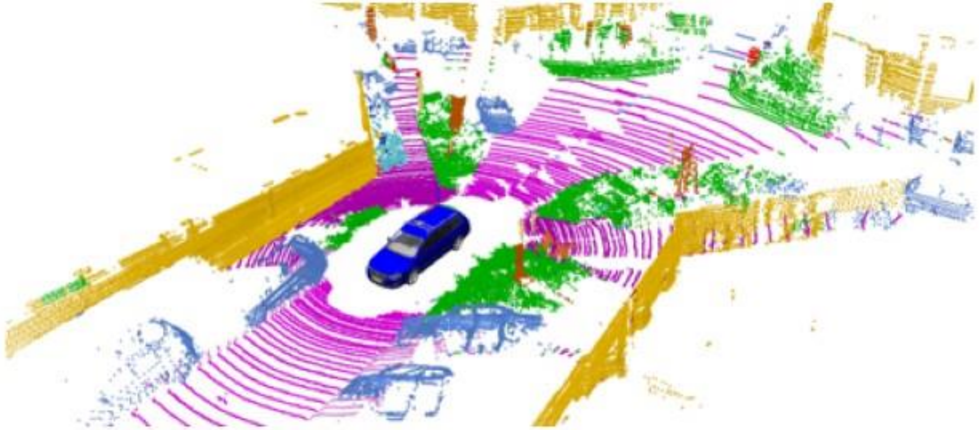
- Back-end：Optimization
  - KeyFrame Retrieval （Loop Closure Detection）
  - Registration


Interactive Map Correction for 3D Graph SLAM

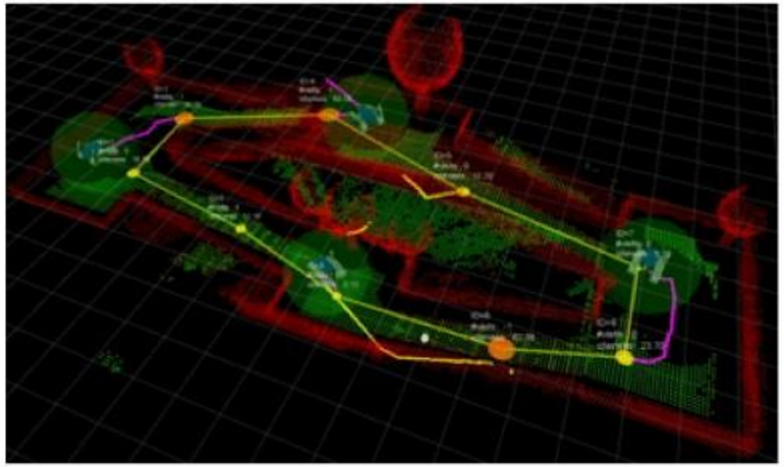
深度学习与激光SLAM的结合点



- Deep Learning in Lidar SLAM
  - ✓ Deep Learning vs Lidar SLAM



- Deep Learning
  - Strong feature extraction capability
  - Strong generalization ability
  - Rich frontier research
  - Black box model,
    fitting optimization,
    lack of precision,
    can not establish error model



- Lidar SLAM
  - High-precision measurement
  - Rigorous mathematical derivation and theory
  - Poor generalization ability in unstructured environment,
    lack of effective point cloud features

内容概要

深度学习与激光SLAM的结合点

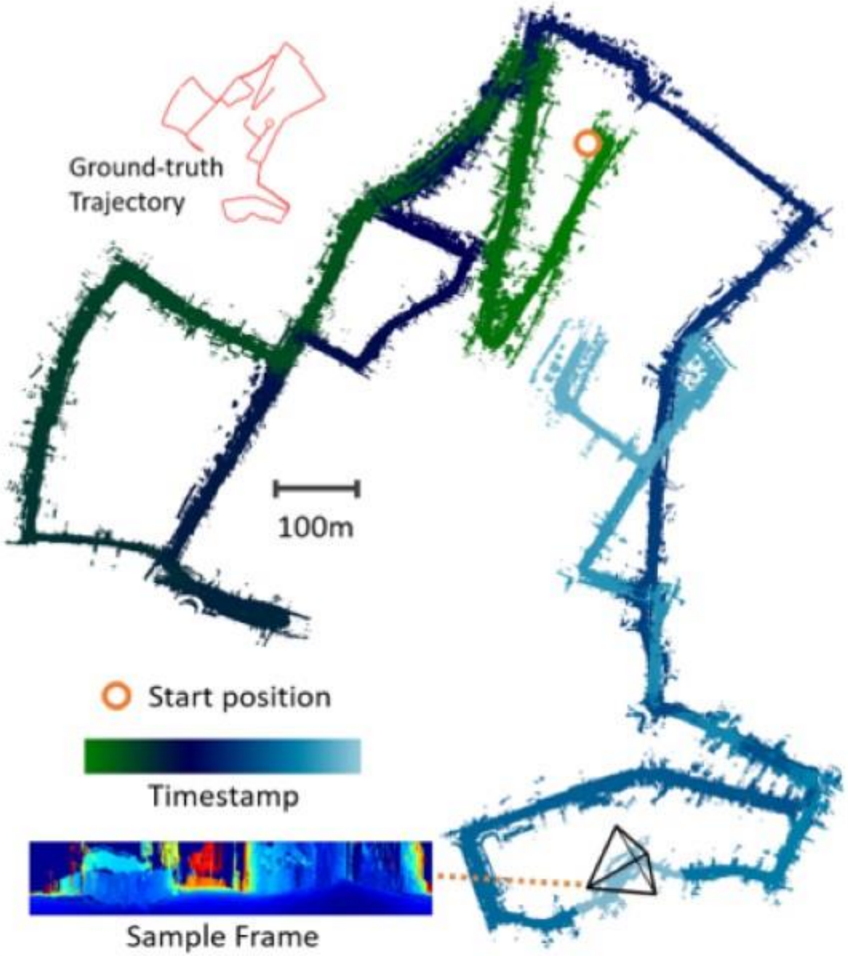
Deep Lidar Odometry

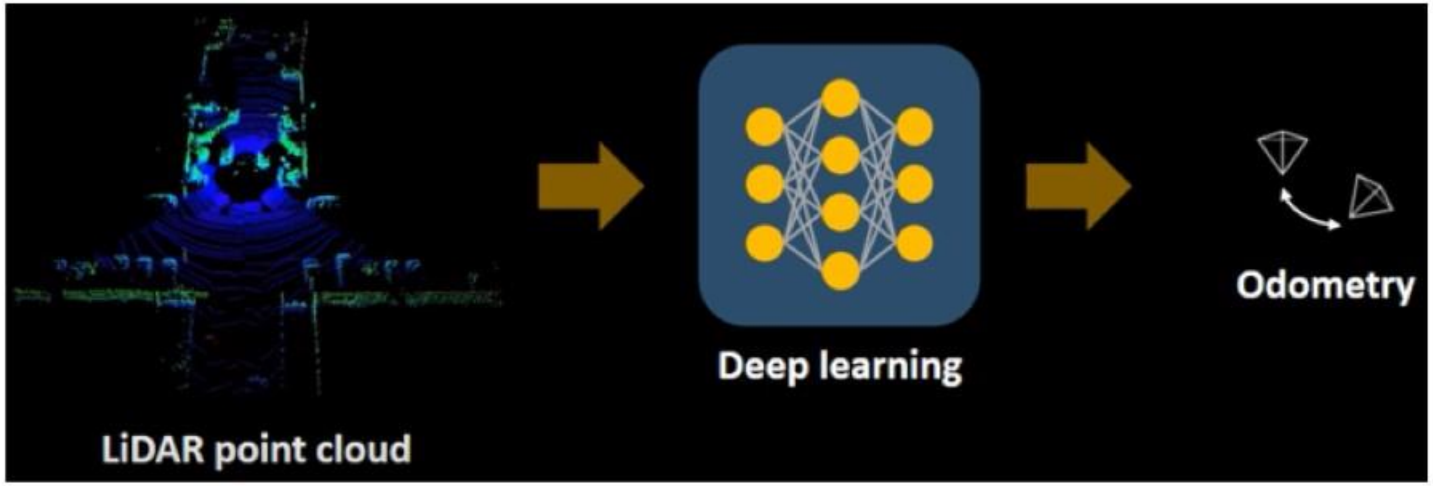
Deep Lidar Loop Closure Detection

Deep Lidar Odometry

➢ DeepLO:Geometry-Aware Deep LiDAR Odometry

✓ DeepLO





Cho Y, Kim G, Kim A. DeepLO: Geometry-Aware Deep LiDAR Odometry[J]. 2019.

Deep Lidar Odometry

➢ DeepLO:Geometry-Aware Deep LiDAR Odometry

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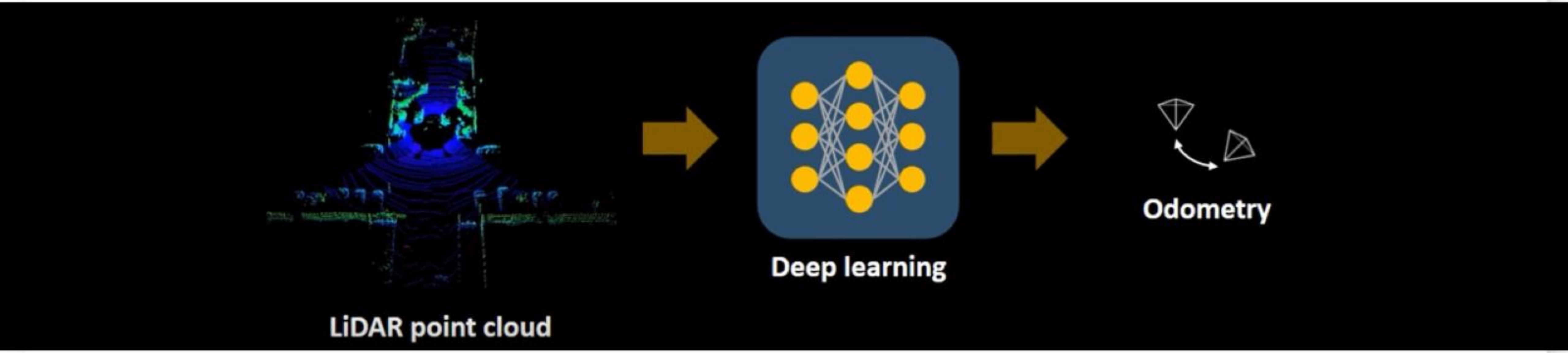

Lidar is accuracy, but …

- Unordered
- Various data type
- Viewpoint dependent scene change

Difficult

- To learn
- To prepare GroundTruth

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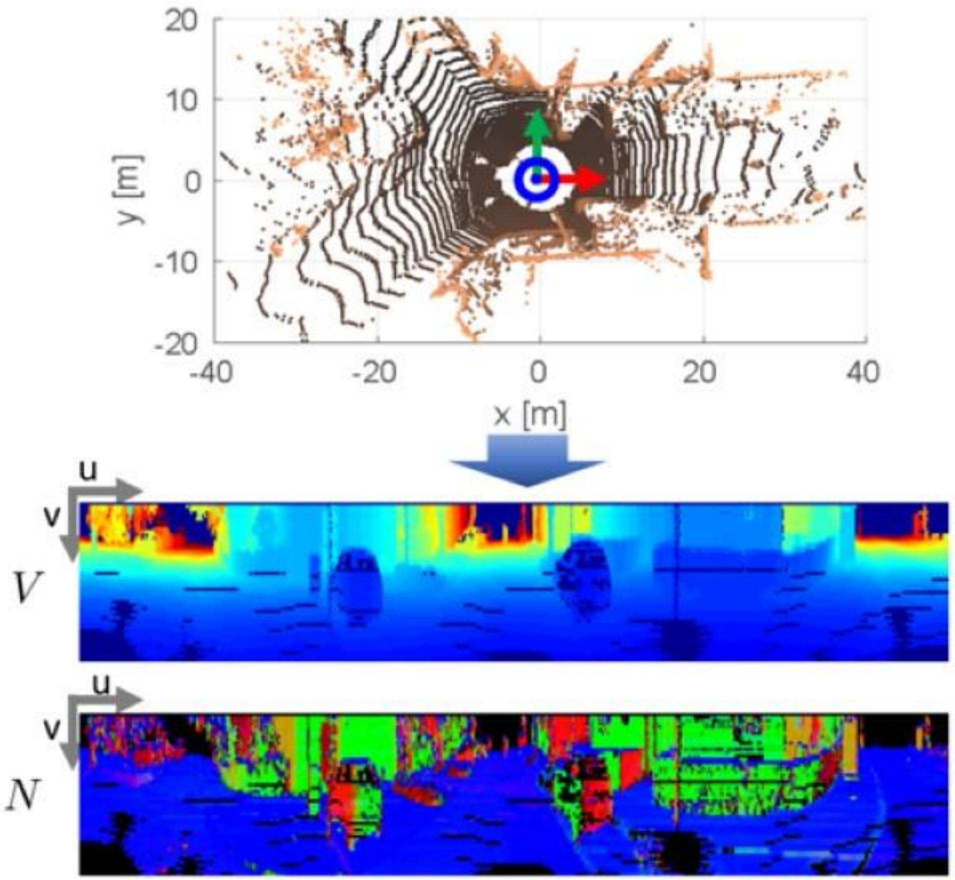

$$\begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} (f_h/2 - \arctan(p^y, p^x))/\delta_h \\ (f_{vu} - \arctan(p^z, d))/\delta_v \end{pmatrix}$$

$$d = ({p^x}^2 + {p^y}^2)^{1/2}$$

f_h Horizontal fielf-of-view

f_v Vertical fielf-of-view

$(u, v) \in \mathbb{R}^2$

$\mathbf{v} = [v^x, v^y, v^z]$

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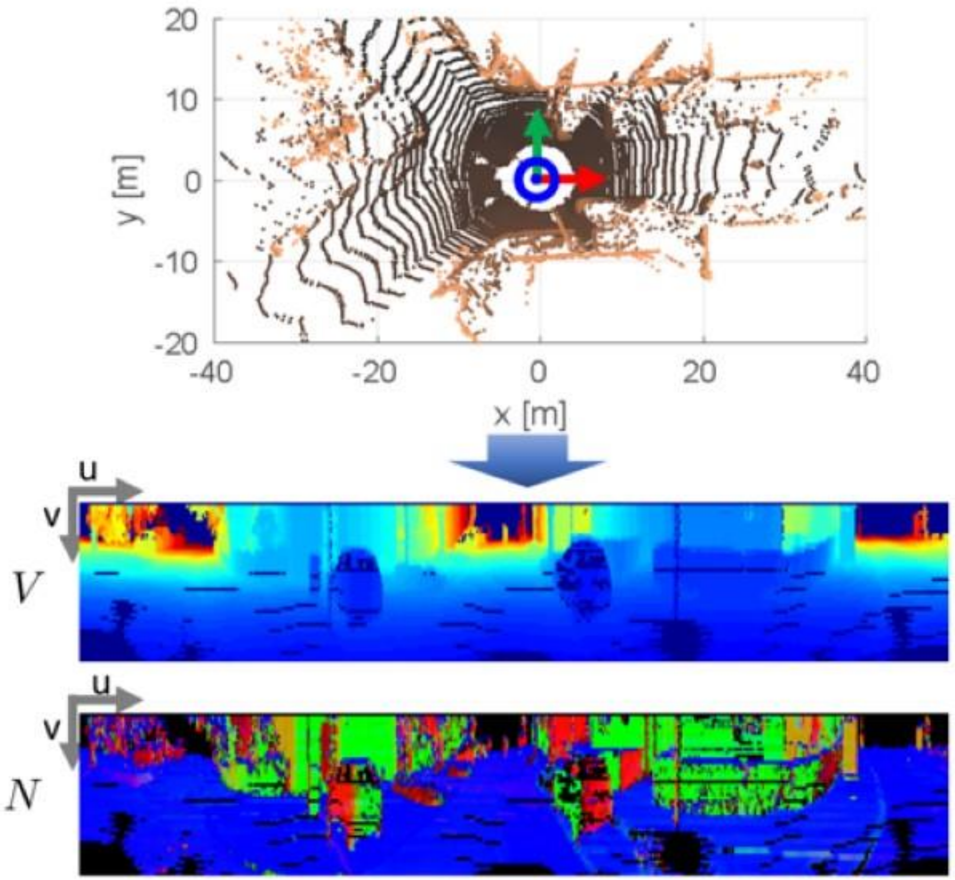
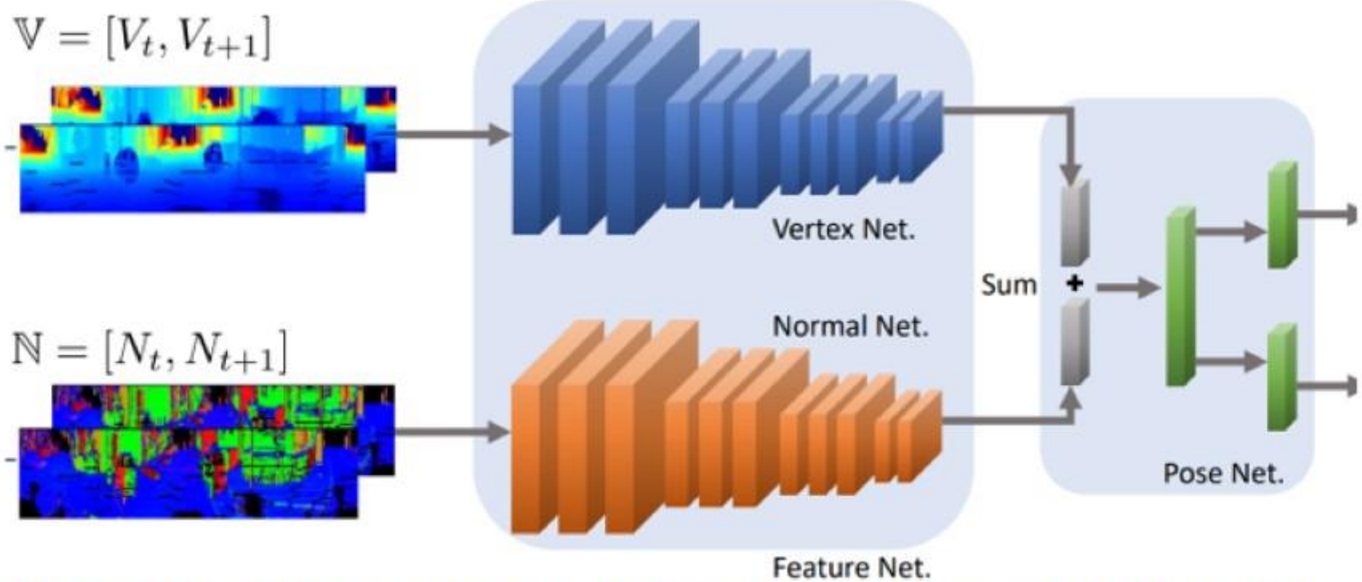




VertexNet and NormalNet are designed based on residual blocks with fully convolutional networks

PoseNet is designed as fully-connected networks that transfer features for metric information, and predicts translation and rotation separately

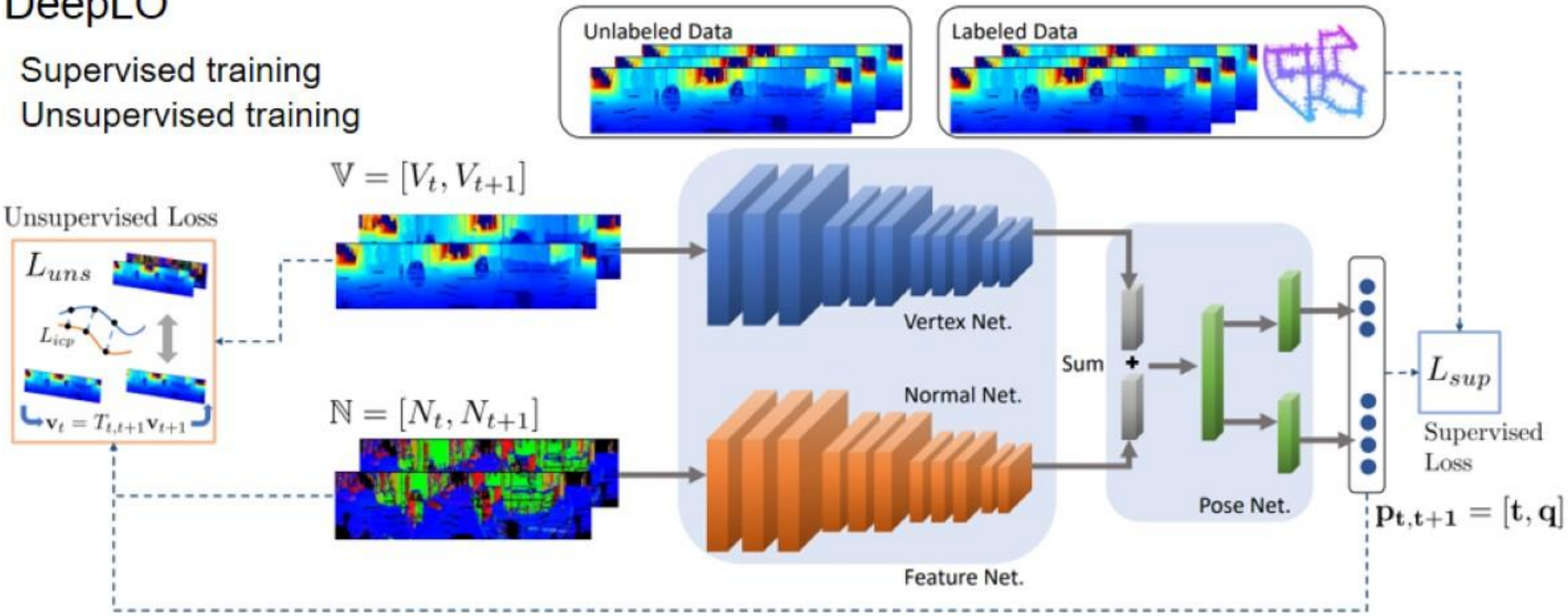
Cho Y, Kim G, Kim A. DeepLO: Geometry-Aware Deep LiDAR Odometry[J]. 2019.

Deep Lidar Odometry

- DeepLO:Geometry-Aware Deep LiDAR Odometry

✓ DeepLO

- Supervised training
- Unsupervised training



$$\mathcal{L}_{sup} = \mathcal{L}_t \exp(-s_t) + s_t + \mathcal{L}_r \exp(-s_r) + s_r$$

$$\mathcal{L}_{icp} = \sum_{\mathbf{v} \in V_{t+1}} \bar{\mathbf{n}}_t \cdot (T_{t,t+1}\mathbf{v}_{t+1} - \bar{\mathbf{v}}_t),$$

$$\mathcal{L}_{uns} = \mathcal{L}_{icp} \exp(-s_{icp}) + s_{icp} + \mathcal{L}_{fov} \exp(-s_{fov}) + s_{fov}$$

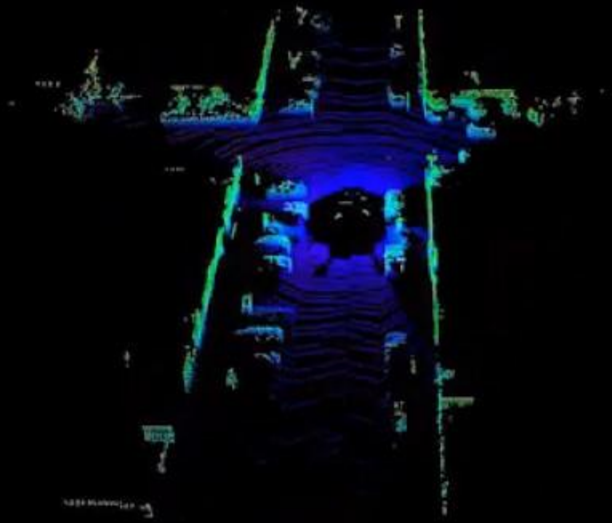
$$\mathcal{L}_{fov} = \sum_{\mathbf{v} \in V_{t+1}} \mathbb{I}(\pi(T_{t,t+1}\mathbf{v}) - (w,h)) + \mathbb{I}(-\pi(T_{t,t+1}))$$

Cho Y, Kim G, Kim A. DeepLO: Geometry-Aware Deep LiDAR Odometry[J]. 2019.

Evaluation on KITTI 00

(DeepLO-Uns)

Current point cloud



Current vertex map
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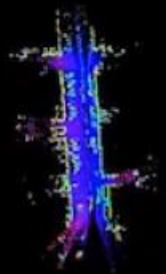


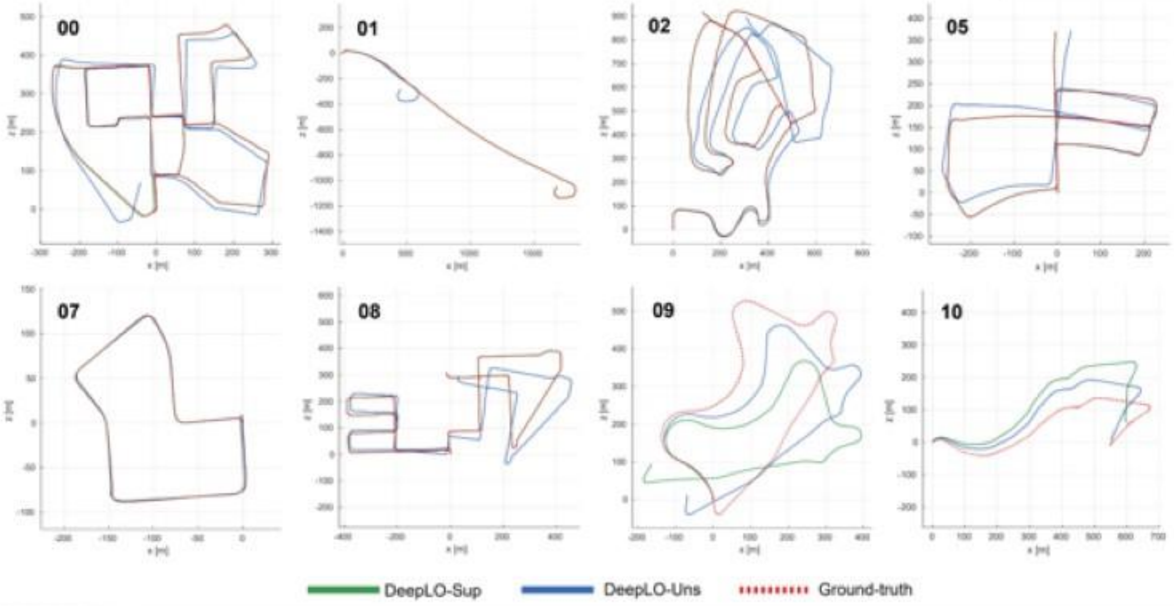
Global trajectory with point clouds

Deep Lidar Odometry

➢ DeepLO:Geometry-Aware Deep LiDAR Odometry

✓ DeepLO

	Sequence	0		1		2		3		4		5	
		t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}
Proposed	DeepLO-Uns	1.90	0.80	37.83	0.86	2.05	0.81	2.85	1.43	1.54	0.87	1.72	0.92
	DeepLO-Sup	0.32	0.12	0.16	0.05	0.15	0.05	0.04	0.01	0.01	0.01	0.11	0.07
Learning-based	Zhu et al. [23]	4.56	2.46	78.98	3.03	5.89	2.16	6.84	2.42	9.12	1.42	3.93	2.09
	SfMLearner [12]	66.35	6.13	35.17	2.74	58.75	3.58	10.78	3.92	4.49	5.24	18.67	4.10
	UnDeepVO [13]	4.41	1.92	69.07	1.60	5.58	2.44	5.00	6.17	4.49	2.13	3.40	1.50
Model-based	SuMa [9]	2.10	0.90	4.00	1.20	2.30	0.80	1.40	0.70	11.90	1.10	1.50	0.80
		6		7		8		9		10			
		t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}	t_{rel}		
Proposed	DeepLO-Uns	0.84	0.47	0.70	0.67	1.81	1.02	6.55	2.19	7.74	2.84		
	DeepLO-Sup	0.03	0.07	0.08	0.05	0.09	0.04	13.35	4.45	5.83	3.53		
Learning-based	Zhu et al. [23]	7.48	3.76	3.13	2.25	4.81	2.24	8.84	2.92	6.65	3.89		
	SfMLearner [12]	25.88	4.80	21.33	6.65	21.90	2.91	18.77	3.21	14.33	3.30		
	UnDeepVO [13]	6.20	1.98	3.15	2.48	4.08	1.79	7.01	3.61	10.63	4.65		
Model-based	SuMa [9]	1.00	0.60	1.80	1.20	2.50	1.00	1.90	0.80	1.80	1.00		



KITTI Odometry evaluation
Translation t_{rel} (%) and rotation r_{rel} (∘/100m) RMSE drift on length of 100m – 800m are presented.

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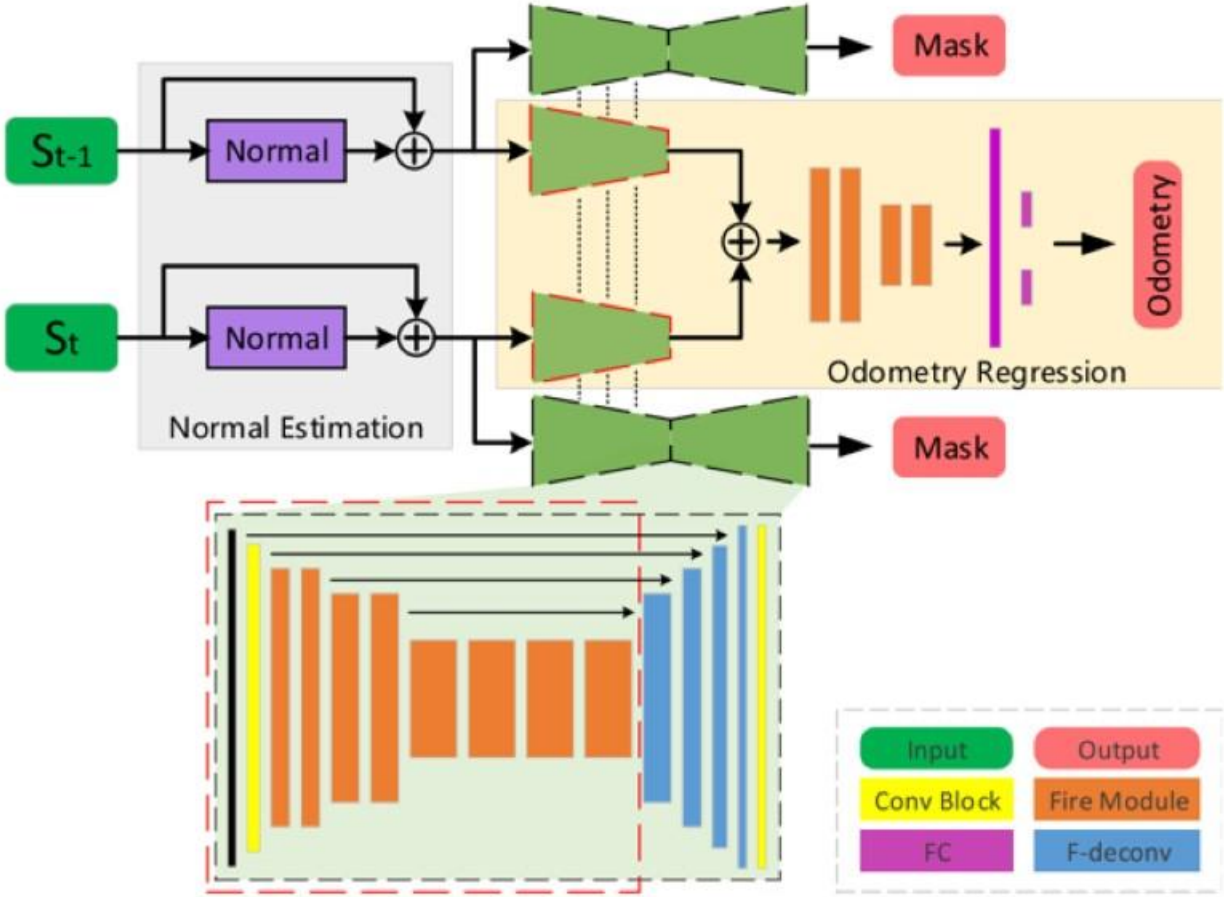
Deep Lidar Odometry

➢ LO-Net: Deep Real-time Lidar Odometry

✓ LO-Net



Li Q, Chen S, Wang C, et al. LO-Net : Deep Real-time Lidar Odometry[J]. .

Deep Lidar Odometry

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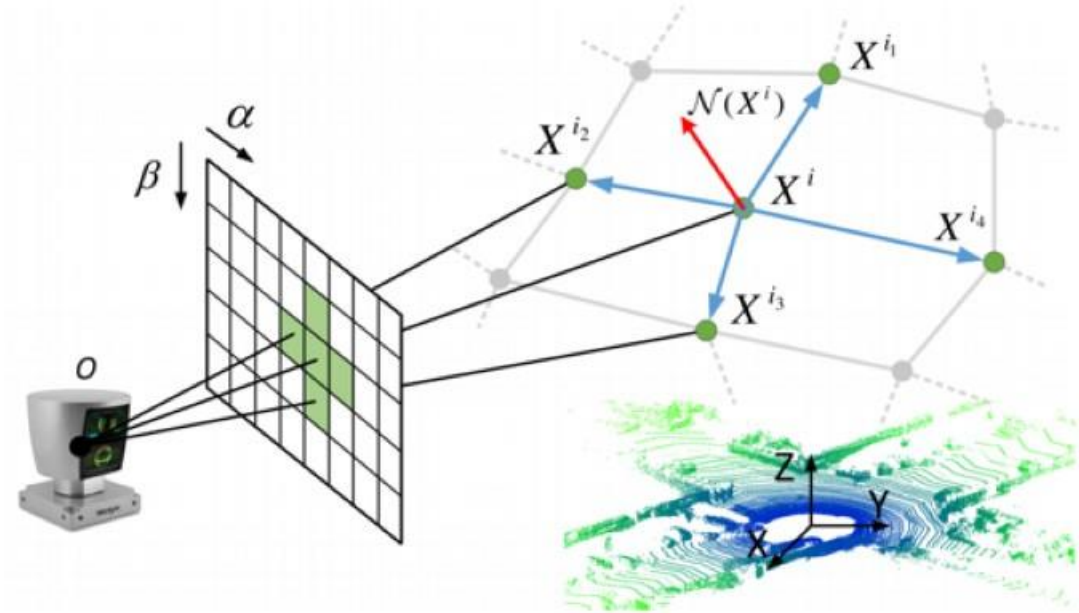

$$\alpha = \arctan(y/x)/\Delta\alpha$$
$$\beta = \arcsin(z/\sqrt{x^2+y^2+z^2})/\Delta\beta$$
$$r = \sqrt{x^2+y^2+z^2}$$
$$H \times W \times C.$$

Normal estimation:

$$\arg\min_{\mathcal{N}(X^i)} \|[w_{i1}(X^{i_1}-X^i), \cdots, w_{ik}(X^{i_k}-X^i)]^T \mathcal{N}(X^i)\|_2$$

$$w_{ik} = \exp(-0.2|r(X^{i_k}) - r(X^i)|)$$

Simiplified Normal estimation:

$$\mathcal{N}(X^i) = \sum_{X^{i_k}, X^{i_j} \in \mathcal{P}} (w_{ik}(X^{i_k}-X^i) \times w_{ij}(X^{i_j}-X^i))$$

Corresponding point elements transformation

$$\hat{X}_t^{\alpha\beta} = P T_t P^{-1} X_{t-1}^{\alpha\beta}$$

Constraint of pose transformation

$$\mathcal{L}_n = \sum_{\alpha\beta} \|\mathcal{N}(\hat{X}_t^{\alpha\beta}) - \mathcal{N}(X_t^{\alpha\beta})\|_1 \cdot e^{|\nabla r(\hat{X}_t^{\alpha\beta})|}$$

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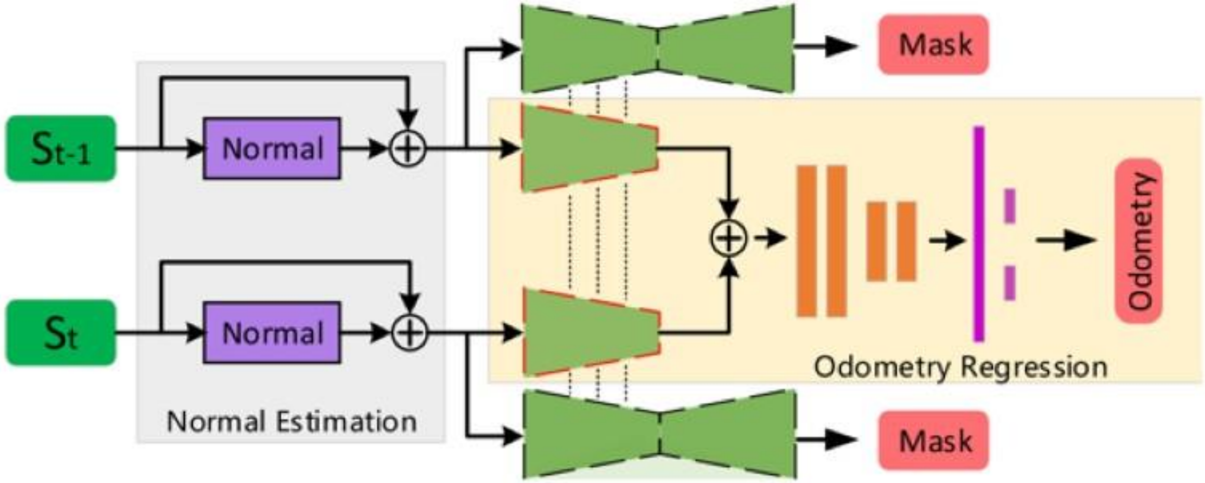
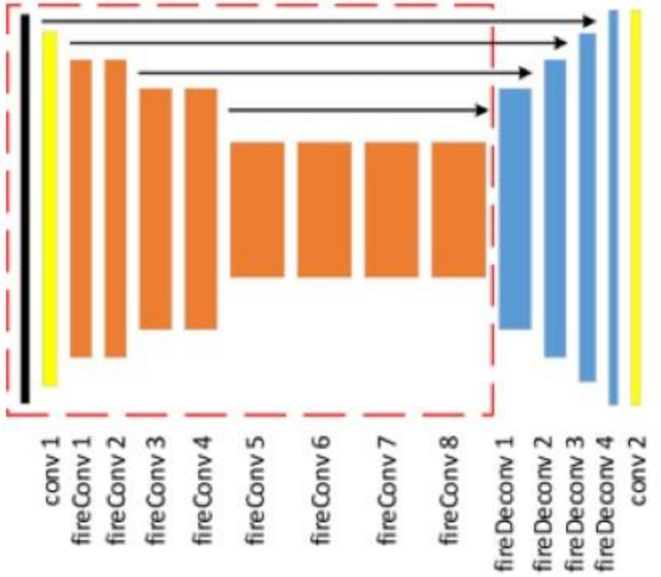
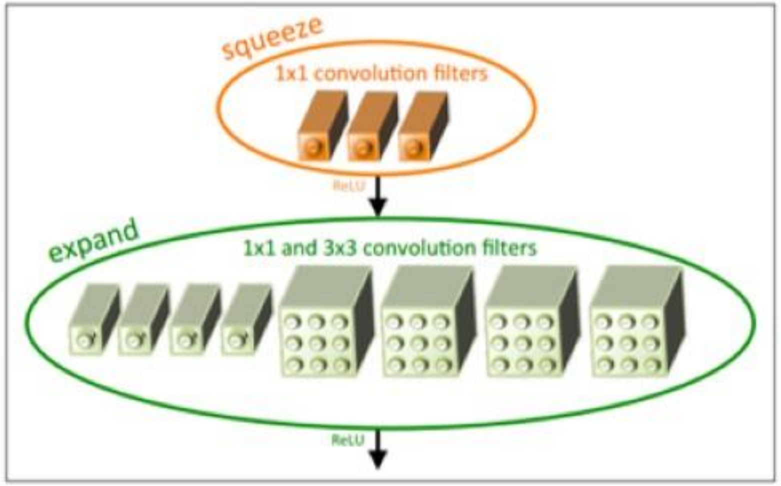




(a) Mask prediction layers



Position and orientation Loss:

$$\mathcal{L}_x(S_{t-1};S_t) = \|x_t - \hat{x}_t\|_l$$

$$\mathcal{L}_q(S_{t-1};S_t) = \left\| q_t - \frac{\hat{q}_t}{\|\hat{q}_t\|} \right\|_l$$

Odometry Loss:

$$\mathcal{L}_o = \mathcal{L}_x(S_{t-1};S_t)\exp(-s_x) + s_x + \mathcal{L}_q(S_{t-1};S_t)\exp(-s_q) + s_q$$

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Deep Lidar Odometry

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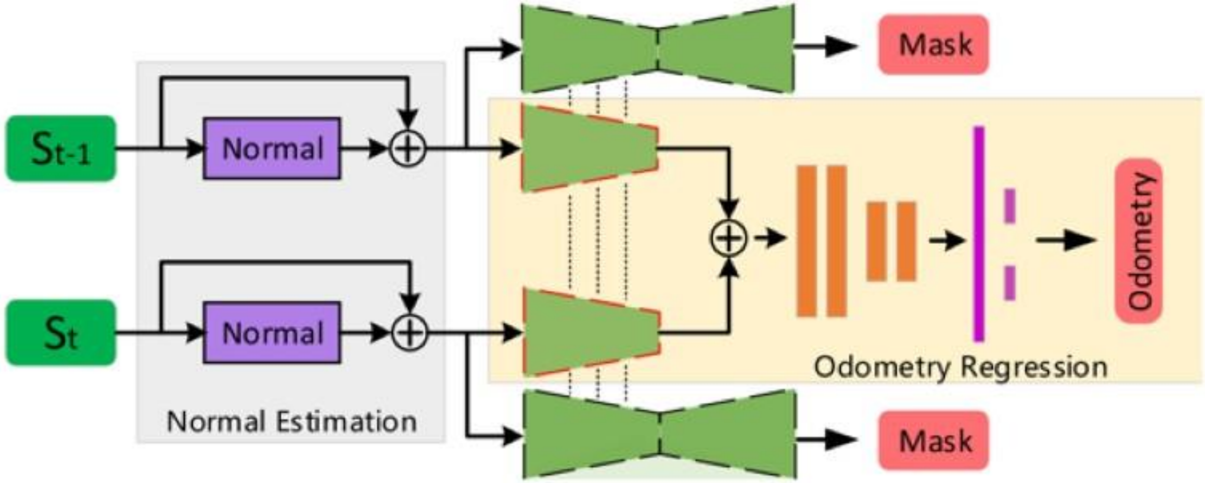

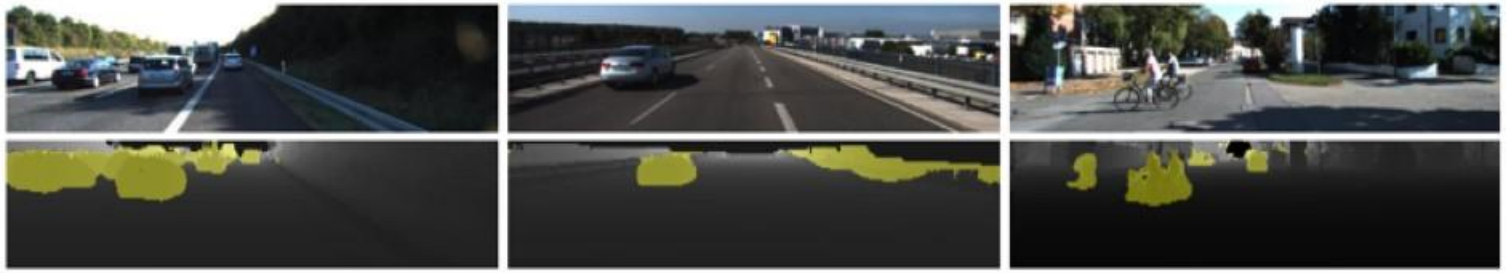

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Odometry Loss:

$$\mathcal{L}_o = \mathcal{L}_x(S_{t-1}; S_t) \exp(-s_x) + s_x + \mathcal{L}_q(S_{t-1}; S_t) \exp(-s_q) + s_q$$

Mask Loss:

$$\mathcal{L}_n = \sum_{\alpha\beta} \mathcal{M}(X_t^{\alpha\beta}) \|\mathcal{N}(\hat{X}_t^{\alpha\beta}) - \mathcal{N}(X_t^{\alpha\beta})\|_1 \cdot e^{|\nabla r(\hat{X}_t^{\alpha\beta})|}$$

Regular Loss:

$$\mathcal{L}_r = -\sum_{\alpha\beta} \log P(\mathcal{M}(X_t^{\alpha\beta}) = 1).$$

$$\mathcal{L} = \mathcal{L}_o + \lambda_n \mathcal{L}_n + \lambda_r \mathcal{L}_r$$

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Deep Lidar Odometry

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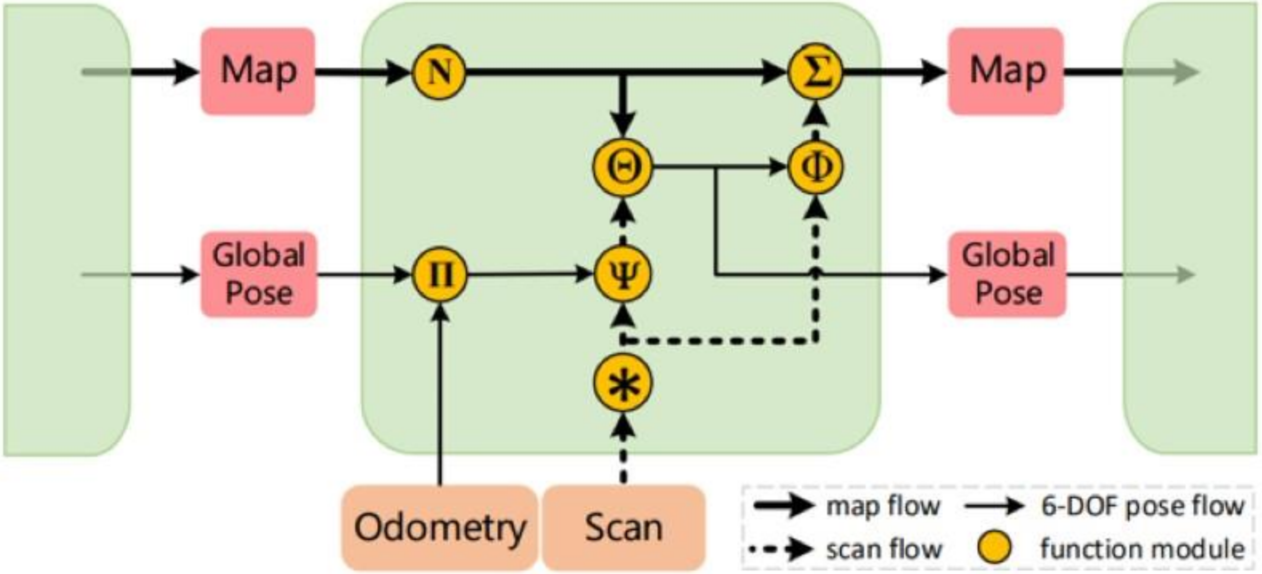

$*$: Based on the normal channels of S_t, we define a term c to evaluate the smoothness of the local area.

$$c = \sum_{k=1}^{3} (K * \mathcal{N}_k)^2$$

K is a 3×5 convolution kernel.
central element is -14, the others are 1.

$\mathbf{\Pi}$: Compute an initial estimate of the lidar pose relative to its first position: $\mathbf{M}_{init} = \mathbf{M}_{t-1}\mathbf{M}_{t-2}^{-1}\mathbf{M}_{t-1}$, where $\mathbf{M}_t$ is the lidar transformation at time t.

Mapping: Scan-to-map Refinement

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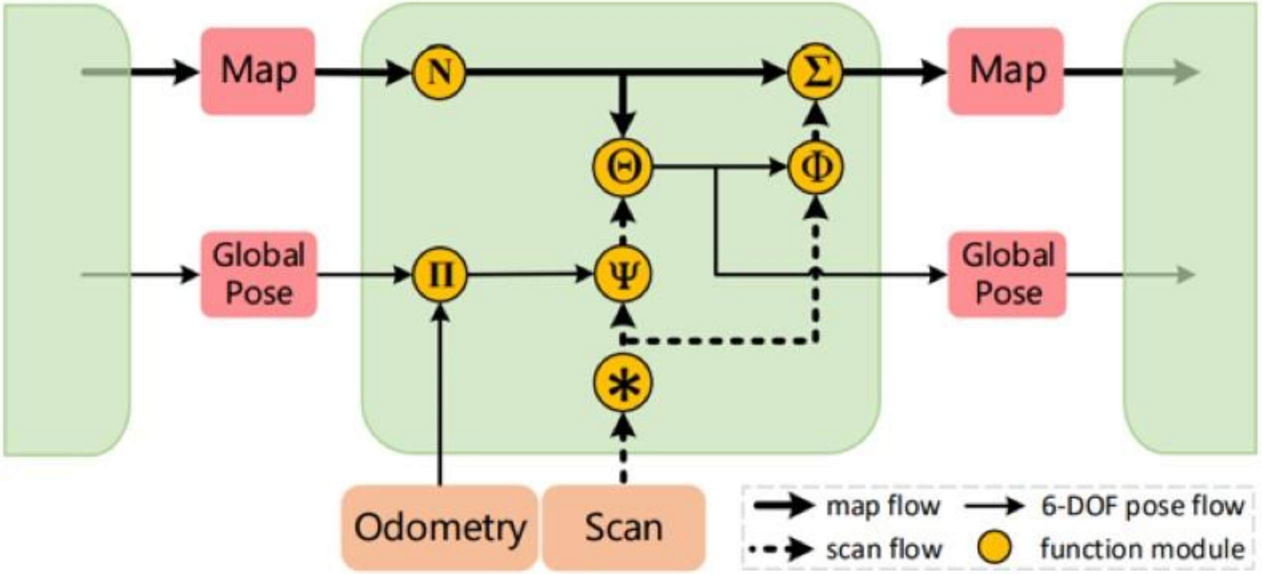

Mapping: Scan-to-map Refinement

$\boldsymbol{\Psi}$: Suppose $\boldsymbol{p}_i = (p_{i_x}, p_{i_y}, p_{i_z}, 1)^T$ is a point in the scan S_t, $\boldsymbol{m}_i = (m_{i_x}, m_{i_y}, m_{i_z}, 1)^T$ is the corresponding point in the map built by the previous scans, $\boldsymbol{n}_i = (n_{i_x}, n_{i_y}, n_{i_z}, 0)^T$ is the unit normal vector at $\boldsymbol{m}_i$. The goal of mapping is to find the optimal 3D rigid-body transformation

$$\hat{\mathbf{M}}_{opt} = \arg\min_{\hat{\mathbf{M}}} \sum_i ((\hat{\mathbf{M}} \cdot \boldsymbol{p}_i - \boldsymbol{m}_i) \cdot \boldsymbol{n}_i)^2 .$$

$\boldsymbol{\Theta}$: Iteratively register the scan onto the map by solving Equation (12) until a maximum number of iteration n_{iter}.

$$\mathbf{M}_t = \prod_{k=1}^{n_{iter}} \hat{\mathbf{M}}_k \mathbf{M}_{init} .$$

$\boldsymbol{\Phi}$: Generate a new point cloud from the current scan S_t by linear interpolation of vehicle motion between $\mathbf{M}_{t-1}$ and $\mathbf{M}_t$.

$\boldsymbol{\Sigma}$, $\mathbf{N}$: Add the new point cloud to the map.

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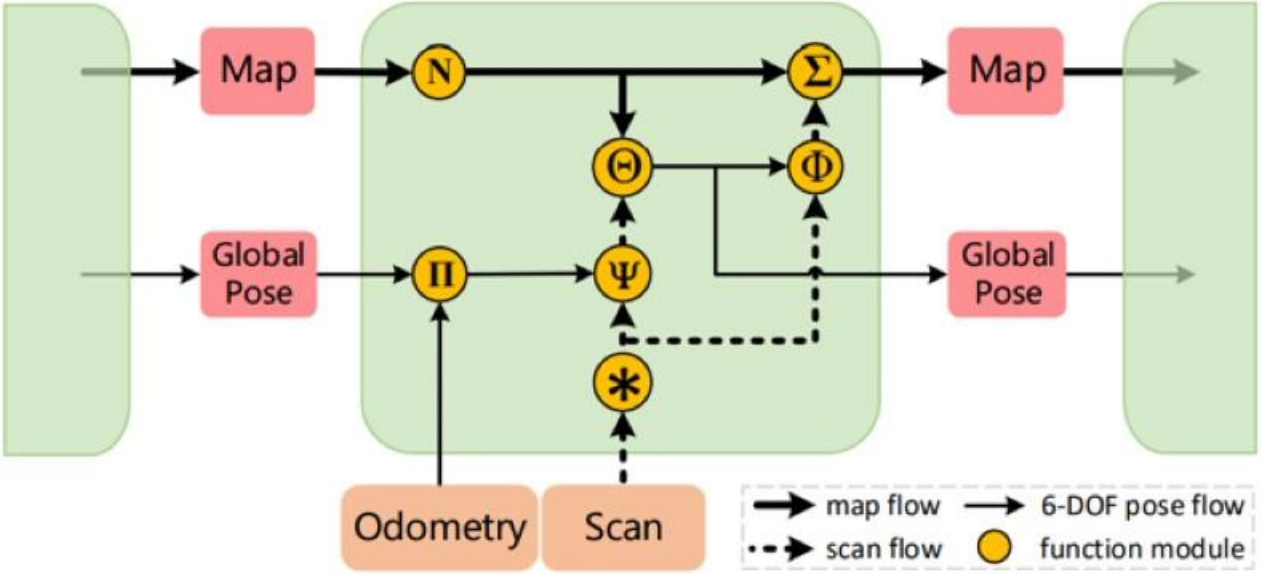
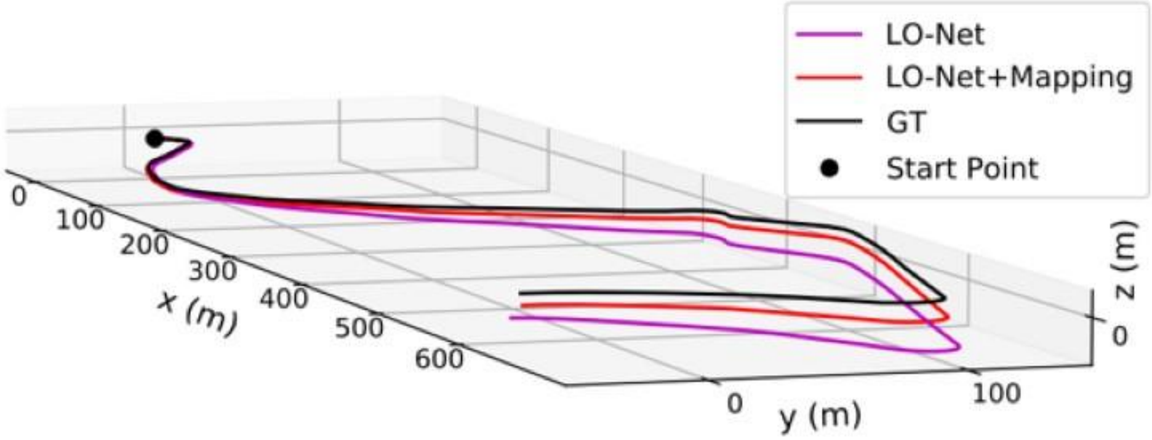




Mapping: Scan-to-map Refinement

Deep Lidar Odometry

➢ LO-Net: Deep Real-time Lidar Odometry

Table 1. Odometry results on KITTI and Ford datasets. Our network is trained on KITTI sequences and then tested on the two datasets.

Seq.	ICP-po2po		ICP-po2pl		GICP [28]		CLS [32]		LOAM [42][1]		Velas *et al.* [33][2]		LO-Net		LO-Net+Mapping	
	t_{rel}	r_{rel}	t_{rel}	r_{rel}	t_{rel}	r_{rel}	t_{rel}	r_{rel}	t_{rel}	r_{rel}	t_{rel}	r_{rel}	t_{rel}	r_{rel}	t_{rel}	r_{rel}
00†	6.88	2.99	3.80	1.73	1.29	0.64	2.11	0.95	1.10 (**0.78**)	0.53	3.02	NA	1.47	0.72	**0.78**	**0.42**
01†	11.21	2.58	13.53	2.58	4.39	0.91	4.22	1.05	2.79 (1.43)	0.55	4.44	NA	**1.36**	0.47	1.42	**0.40**
02†	8.21	3.39	9.00	2.74	2.53	0.77	2.29	0.86	1.54 (**0.92**)	0.55	3.42	NA	1.52	0.71	1.01	**0.45**
03†	11.07	5.05	2.72	1.63	1.68	1.08	1.63	1.09	1.13 (0.86)	0.65	4.94	NA	1.03	0.66	**0.73**	**0.59**
04†	6.64	4.02	2.96	2.58	3.76	1.07	1.59	0.71	1.45 (0.71)	**0.50**	1.77	NA	**0.51**	0.65	0.56	0.54
05†	3.97	1.93	2.29	1.08	1.02	0.54	1.98	0.92	0.75 (**0.57**)	0.38	2.35	NA	1.04	0.69	0.62	**0.35**
06†	1.95	1.59	1.77	1.00	0.92	0.46	0.92	0.46	0.72 (0.65)	0.39	1.88	NA	0.71	0.50	**0.55**	**0.33**
07*	5.17	3.35	1.55	1.42	0.64	0.45	1.04	0.73	0.69 (0.63)	0.50	1.77	NA	1.70	0.89	**0.56**	**0.45**
08*	10.04	4.93	4.42	2.14	1.58	0.75	2.14	1.05	1.18 (1.12)	0.44	2.89	NA	2.12	0.77	**1.08**	**0.43**
09*	6.93	2.89	3.95	1.71	1.97	0.77	1.95	0.92	1.20 (**0.77**)	0.48	4.94	NA	1.37	0.58	**0.77**	**0.38**
10*	8.91	4.74	6.13	2.60	1.31	0.62	3.46	1.28	1.51 (**0.79**)	0.57	3.27	NA	1.80	0.93	0.92	**0.41**
mean†	7.13	3.08	5.15	1.91	2.23	0.78	2.11	0.86	1.35 (0.85)	0.51	3.12	NA	1.09	0.63	**0.81**	**0.44**
mean*	7.76	3.98	4.01	1.97	1.38	0.65	2.15	1.00	1.15 (**0.83**)	0.50	3.22	NA	1.75	0.79	**0.83**	**0.42**
Ford-1	8.20	2.64	3.35	1.65	3.07	1.17	10.54	3.90	1.68	0.54	NA	NA	2.27	0.62	**1.10**	**0.50**
Ford-2	16.23	2.84	5.68	1.96	5.11	1.47	14.78	4.60	1.78	0.49	NA	NA	2.18	0.59	**1.29**	**0.44**

[1]: The results on KITTI dataset outside the brackets are obtained by running the code, and those in the brackets are taken from [42].

[2]: The results on KITTI dataset are taken from [33], and the results on Ford dataset are not available.

†: The sequences of KITTI dataset that are used to train LO-Net.

*: The sequences of KITTI dataset that are not used to train LO-Net.

t_{rel}: Average translational RMSE (%) on length of 100m-800m.

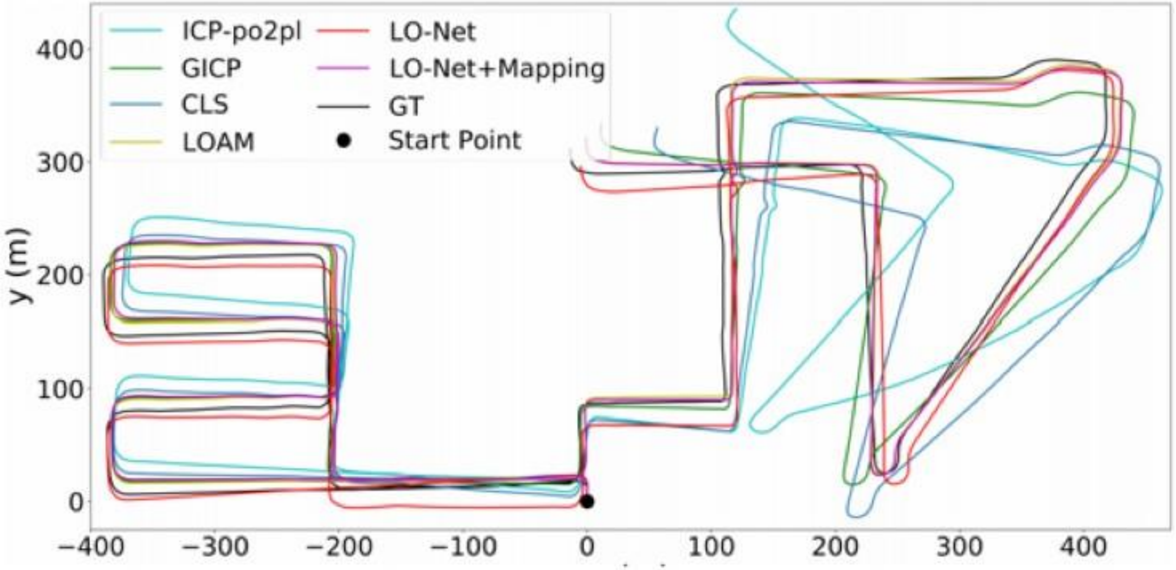
r_{rel}: Average rotational RMSE ($^\circ$/100m) on length of 100m-800m.

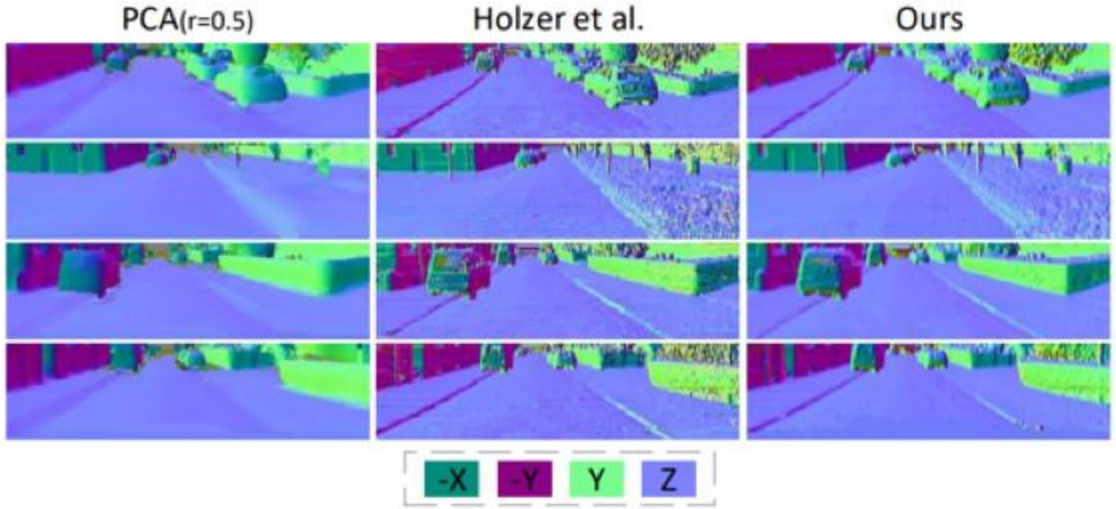
Li Q, Chen S, Wang C, et al. LO-Net : Deep Real-time Lidar Odometry[J]. .

Deep Lidar Odometry

➢ LO-Net: Deep Real-time Lidar Odometry

✓ LO-Net





Trajectory plots of KITTI Seq. 08 with ground truth. LO-Net+Mapping produces most accurate trajectory

Visual comparison of normal results on KITTI dataset.

内容概要

深度学习与激光SLAM的结合点

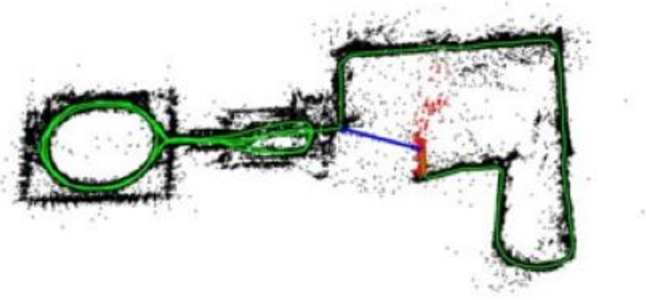
Deep Lidar Odometry

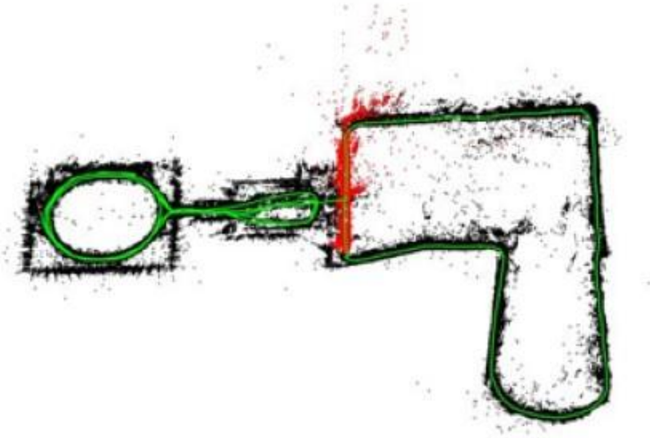
Deep Lidar Loop Closure Detection

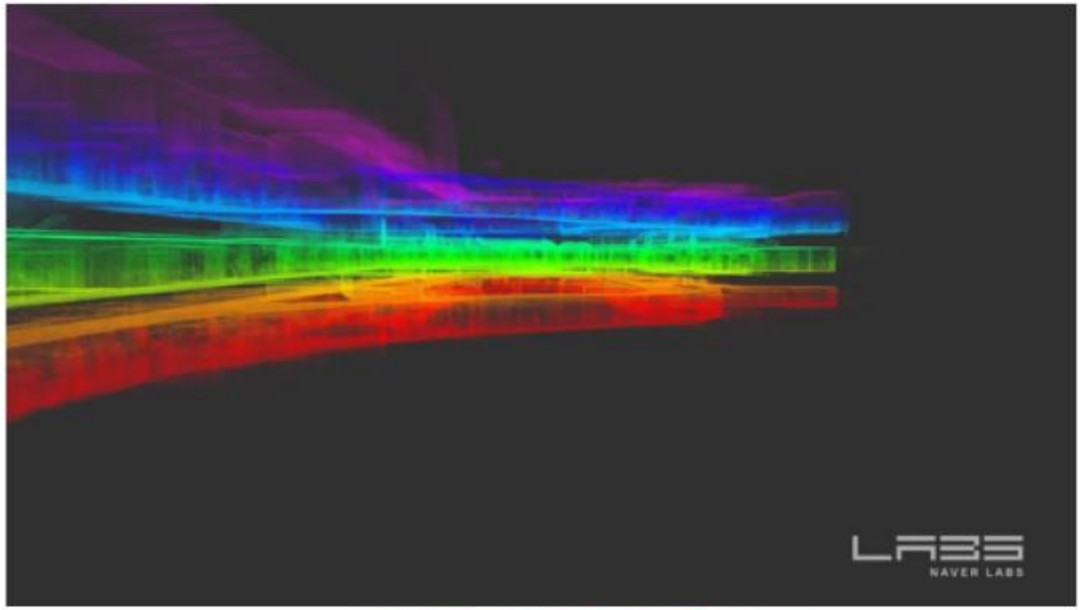
Deep Lidar Loop Closure Detection

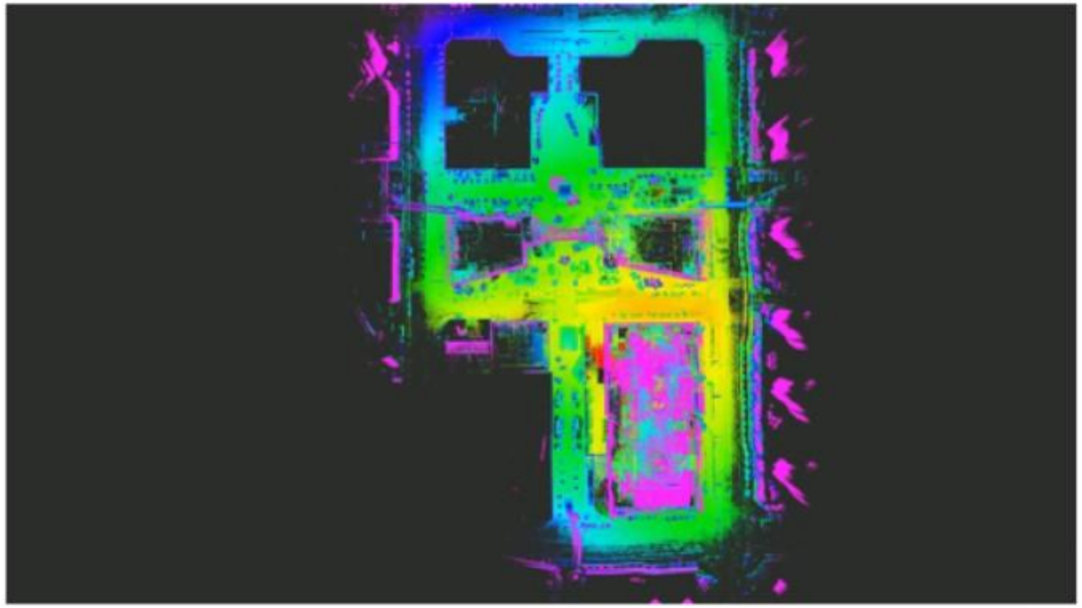
- Loop Closure Detection

  ✓ Representation:
  - PointNetVLAD
  - PCAN
  - LPD-Net
  - PIC-Net







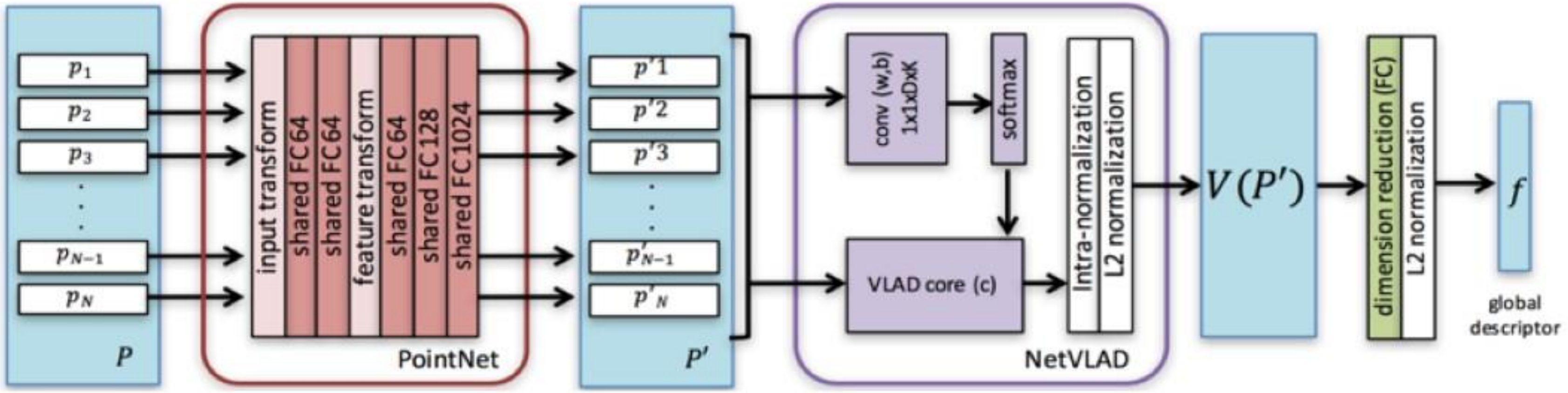


Deep Lidar Loop Closure Detection

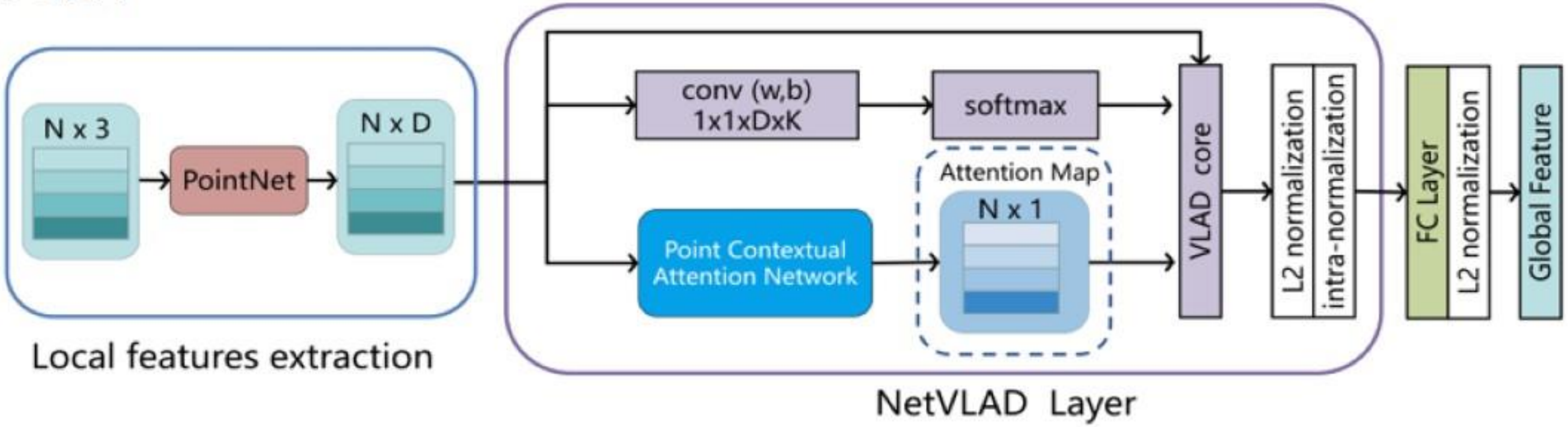
- Loop Closure Detection

  - Representation:
    - PointNetVLAD
    - PCAN

PointNetVLAD



PCAN

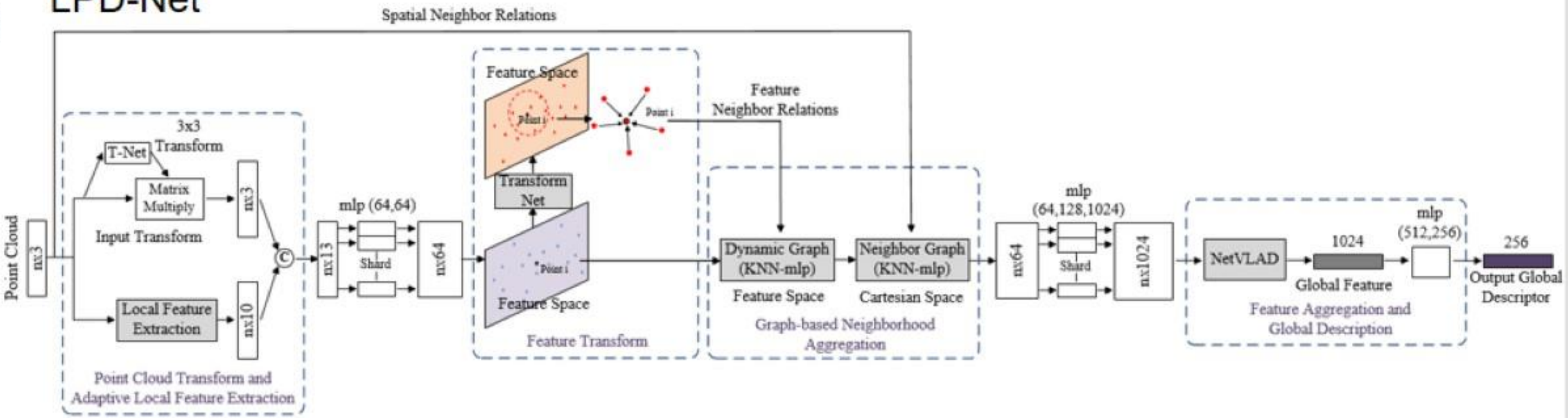


Deep Lidar Loop Closure Detection

- Loop Closure Detection

✓ Representation：
- LPD-Net
- PIC-Net

LPD-Net



PIC-Net