

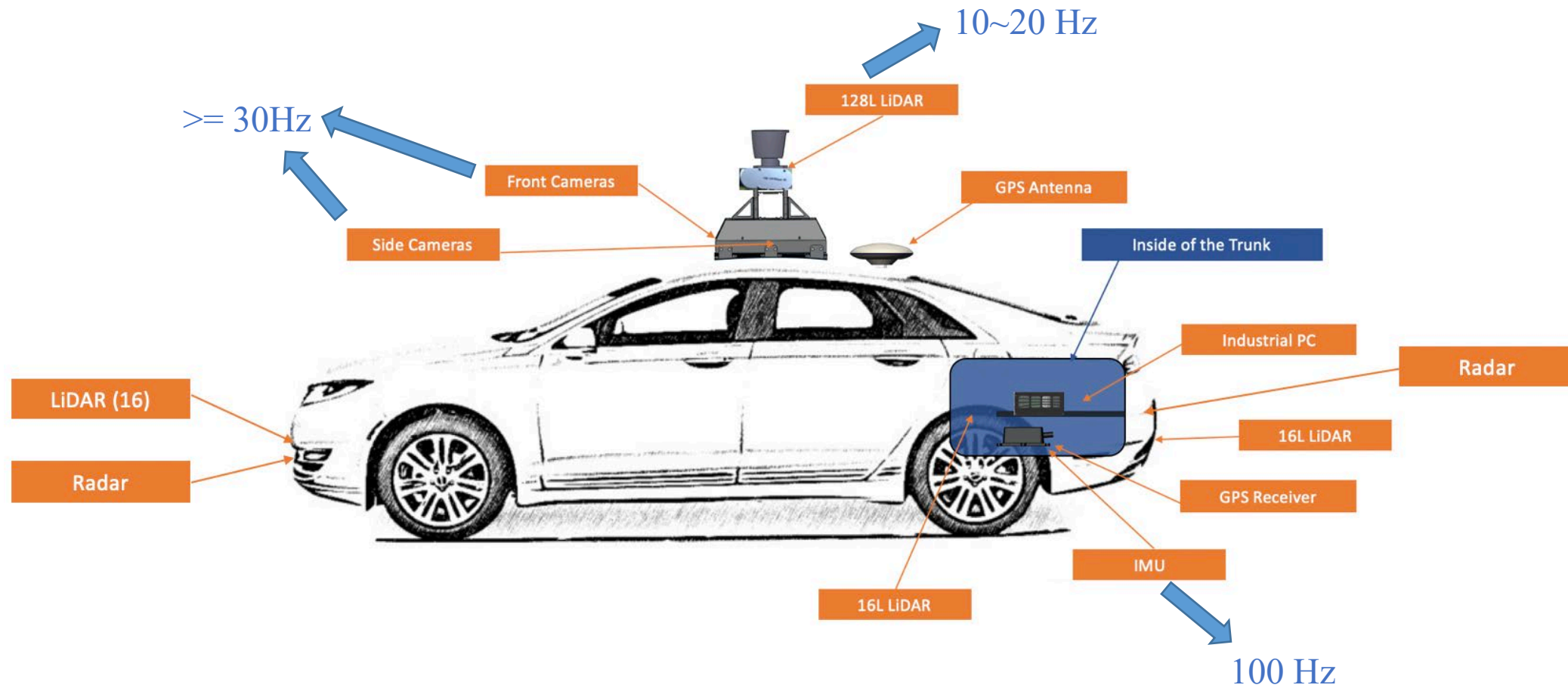


# PointINet: Point Cloud Frame Interpolation Network

Fan Lu, Guang Chen, Sanqing Qu, Zhijun Li, Yinlong Liu, Alois Knoll

Institute of Intelligent Vehicles, Tongji University

## Typical hardware architecture of autonomous vehicle (Apollo from Baidu)



## What can low frame rate of LiDAR sensors cause ?

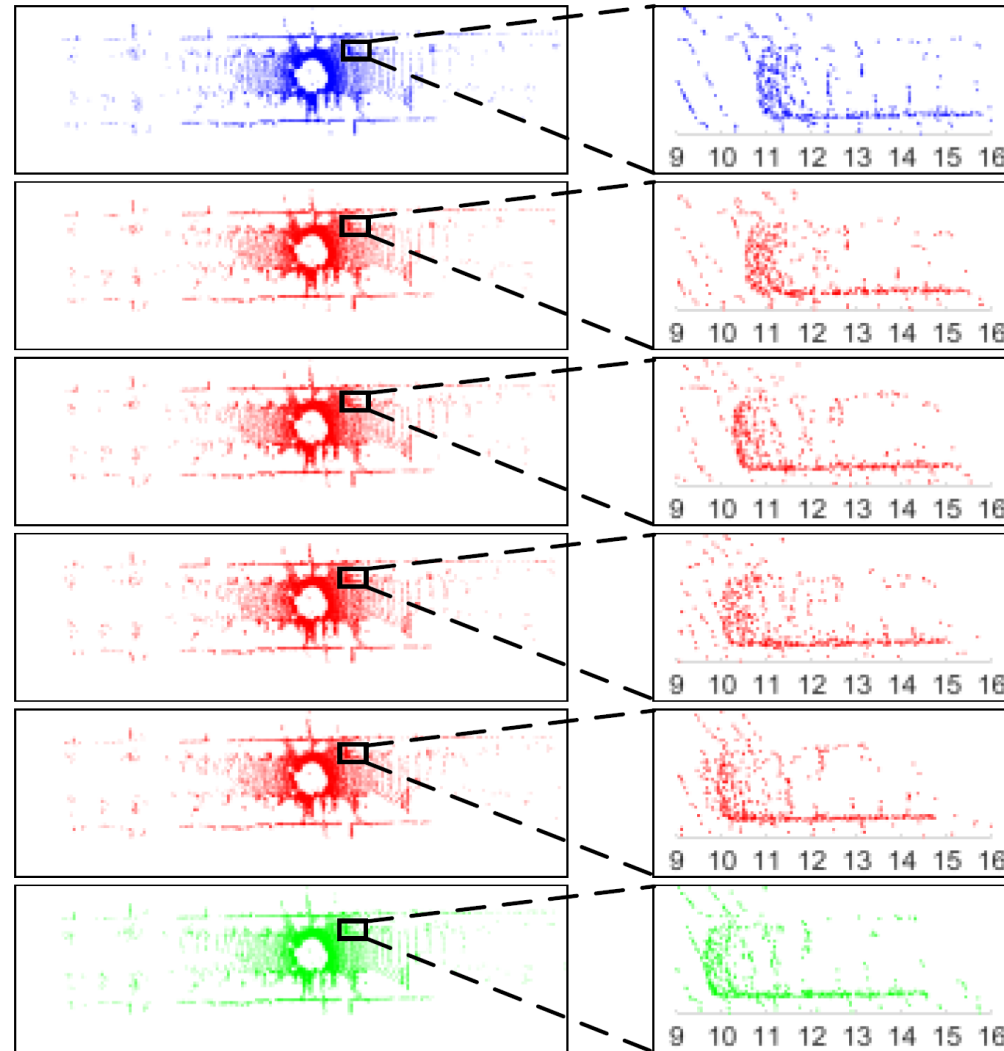
- Discontinuity of point cloud streams
- Difficulty to synchronize LiDAR with other sensors (camera/IMU)

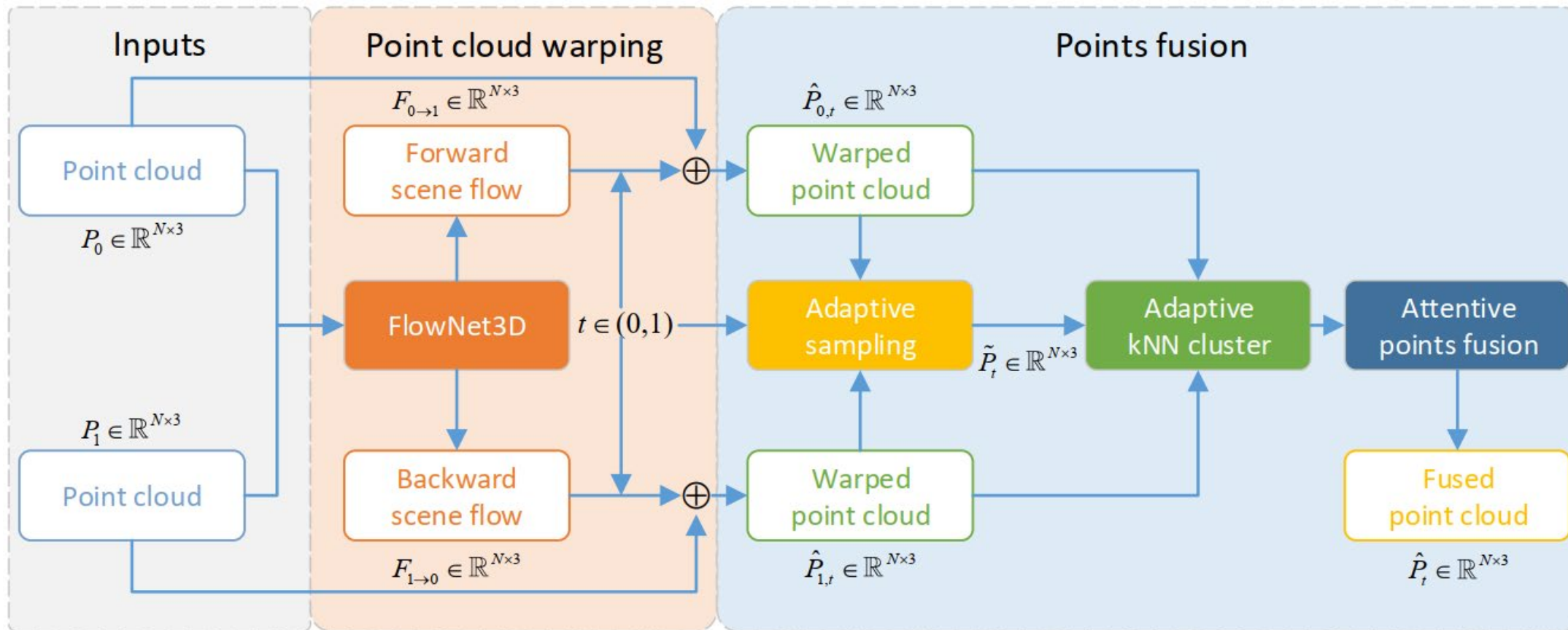
## How to solve ?

- The frame rate of mechanical LiDAR is limited by the hardware performance.
- Can we increase the frame rate of LiDAR point cloud through algorithm ?

## Point Cloud Frame Interpolation

Given two consecutive point clouds, the proposed new task aims to predict intermediate frame(s) between them, which can increase the frame rate of LiDAR sensors by algorithm.





## Point cloud warping

**Objective:** Warp the two point clouds to the given time step.

- Estimate 3D scene flow  $F_{0 \rightarrow 1}$  and  $F_{1 \rightarrow 0}$  between two consecutive point clouds.  
(based on FlowNet3D [1])
- Warping the two point cloud based on linear motion assumption.

$$F_{0 \rightarrow t} = t \times F_{0 \rightarrow 1}$$

$$\hat{P}_{0,t} = P_0 + F_{0 \rightarrow t}$$

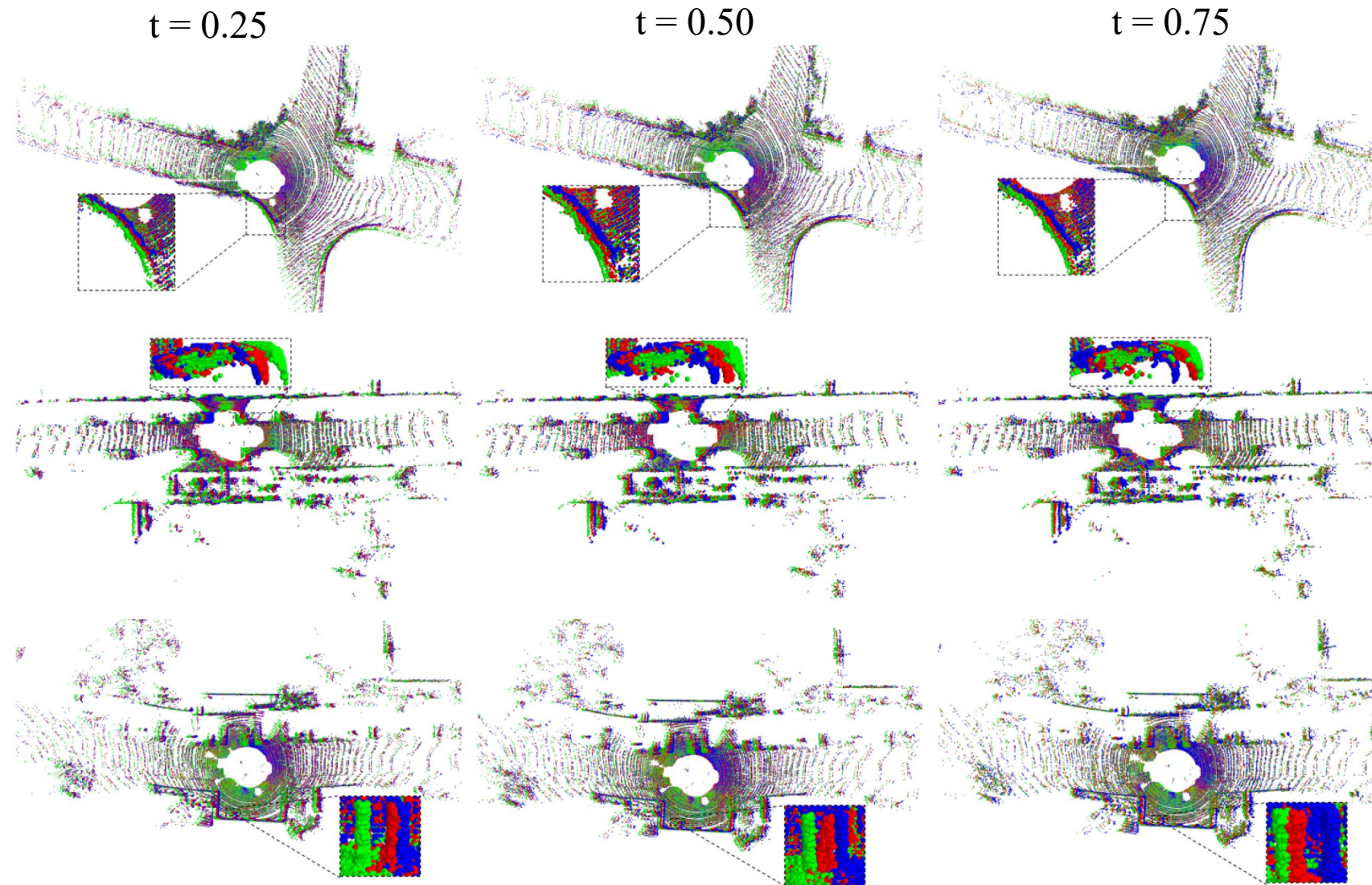
$$F_{1 \rightarrow t} = (1 - t) \times F_{1 \rightarrow 0}$$

$$\hat{P}_{1,t} = P_1 + F_{1 \rightarrow t}$$

## Points fusion

**Objective:** Fuse the two warped point clouds.

- **Adaptive sampling:** randomly sample  $(1 - t) \times N$  points from first point cloud and  $t \times N$  points from second point cloud to form a new point cloud.
- **Adaptive  $k$ NN cluster:** generate  $k$ NN clusters for each point in the formed point cloud and the number of queried points in two warped point clouds are adaptively adjusted according to the time step  $t$ .
- **Attentive points fusion:** predict attentive weights for each point in the cluster and the new point is calculated as the weighted sum of neighbor points.





## Quantitative evaluation

**Metrics:** Chamfer distance and Earth mover's distance

**Baseline methods:** Identity, Align-ICP, Scene flow

**Ground truth:** Downsample 10 Hz point clouds to 2 Hz and 20 Hz point clouds to 4 Hz and then interpolate them to original ones.

Quantitative results on Kitti odometry dataset

Metric	Identity	Align-ICP	Scene flow	Ours
CD↓	1.398	0.752	0.687	<b>0.457</b>
EMD↓	68.93	83.79	57.13	<b>39.46</b>

Quantitative results on nusenes dataset

Metric	Identity	Align-ICP	Scene flow	Ours
CD↓	0.617	0.555	0.511	<b>0.487</b>
EMD↓	54.24	51.12	50.97	<b>47.98</b>

## Experiments on applications

Downsample the original point clouds to low frame rate ones and then interpolate them to original frame rates, and compare the performance of applications on original and interpolated point clouds.

**Keypoints detection:** detect 3D keypoints (Harris-3D, SIFT-3D, ISS) in point clouds and calculate the **repeatability**.

Keypoints	Harris-3D	SIFT-3D	ISS
Original	0.155	0.174	0.163
Interpolated	0.138	0.151	0.133

**Multi frame ICP:** utilize ICP algorithm to estimate the relative pose between two point clouds and accumulatively estimate the relative pose of multi frames. Relative translation error and relative rotation error are calculated.

Results on Kitti odometry dataset

Metric	Original	Interpolated	Difference
RTE (m)	4.31	4.57	0.26
RRE (deg)	2.70	2.95	0.25

Results on Nuscenes dataset

Metric	Original	Interpolated	Difference
RTE (m)	1.65	1.72	0.07
RRE (deg)	0.91	0.92	0.01

**Thank you !**