LiDAR 누적 기반 고밀도 점군데이터 생성을 통한 정밀한 깊이 완성 기법

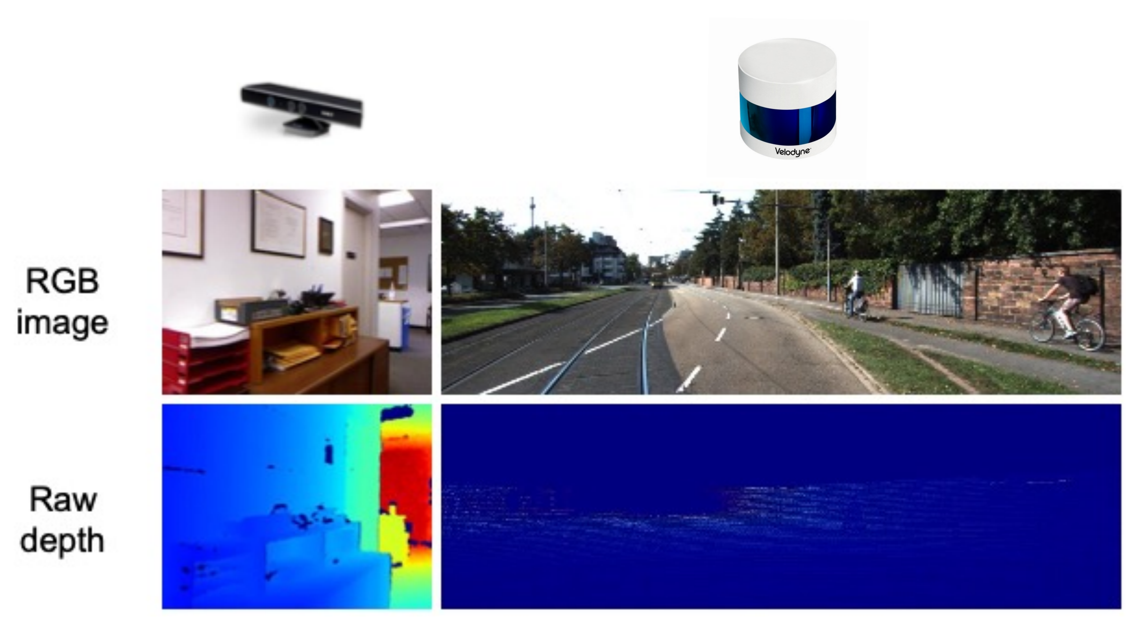
Towards precise depth completion guided by dense point cloud based on LiDAR Accumulation

김 석 영1) · 박 영 규1) · 박 태 현1) · 서 유 리2) · 김 찬 수*3) · 김 성 준4) · 조 기 춘4)

전남대학교 IoT인공지능융합전공1) · 전남대학교 인공지능학부2) · 전남대학교 지능형모빌리티융합학과3) · 건국대학교 스마트운행체공학과4)

Introduction

- Estimating accurate depth of a scene is one of the core problem to solve in Autonomous Driving, Computer Vision, Robotics, etc.
- Depth sensors such as LiDAR or Stereo Camera both similar downside, which that their observation is sparse.



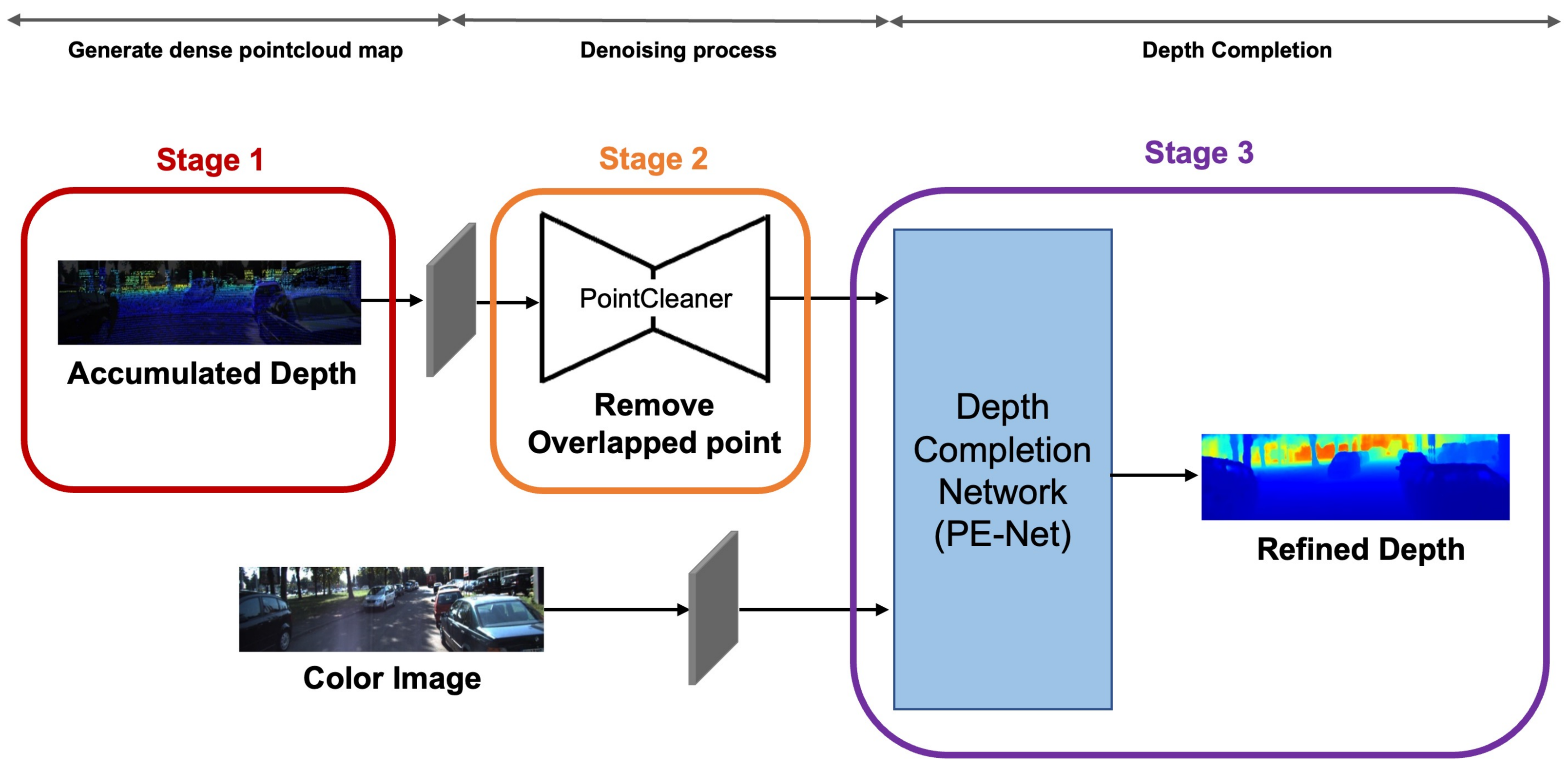
- In order to perform effective depth completion, we tries to accumulate sparse inputs based on LiDAR SLAM. The noise generated by accumulation is removed through our proposed network(*PointCleaner*), which is to give depth guidance by more dense and rich depth completion input.

Contribution

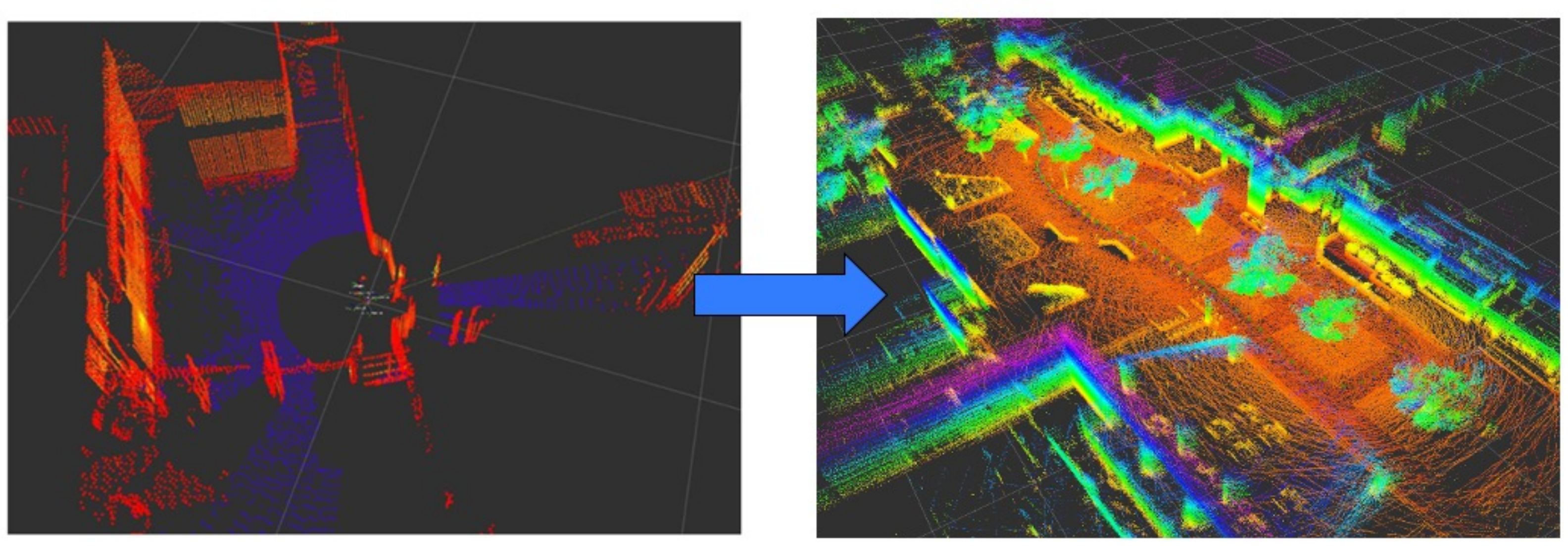
- Design a SLAM Preprocessing based depth completion framework
- Propose a new network for remove overlapped point of accumulated depth

Proposed Method

- Model Architecture

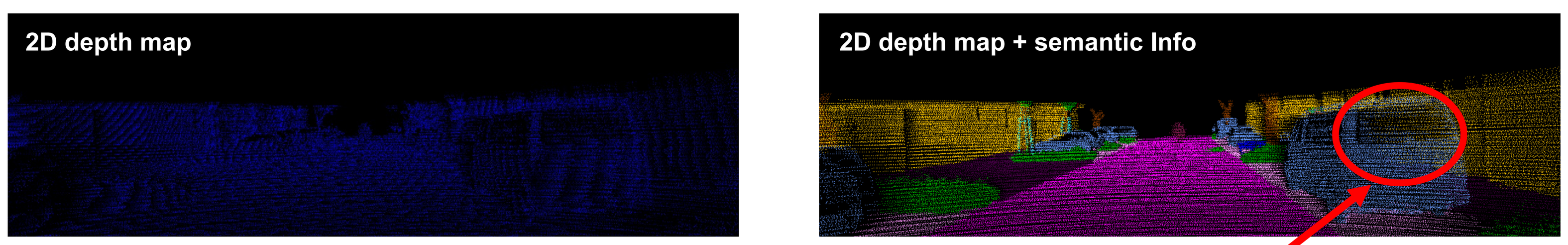


- **Stage 1** : Accumulate LiDAR scans for 10 scans using SLAM (*Suma++*)



Sparse 3D pointcloud map Dense 3D pointcloud map

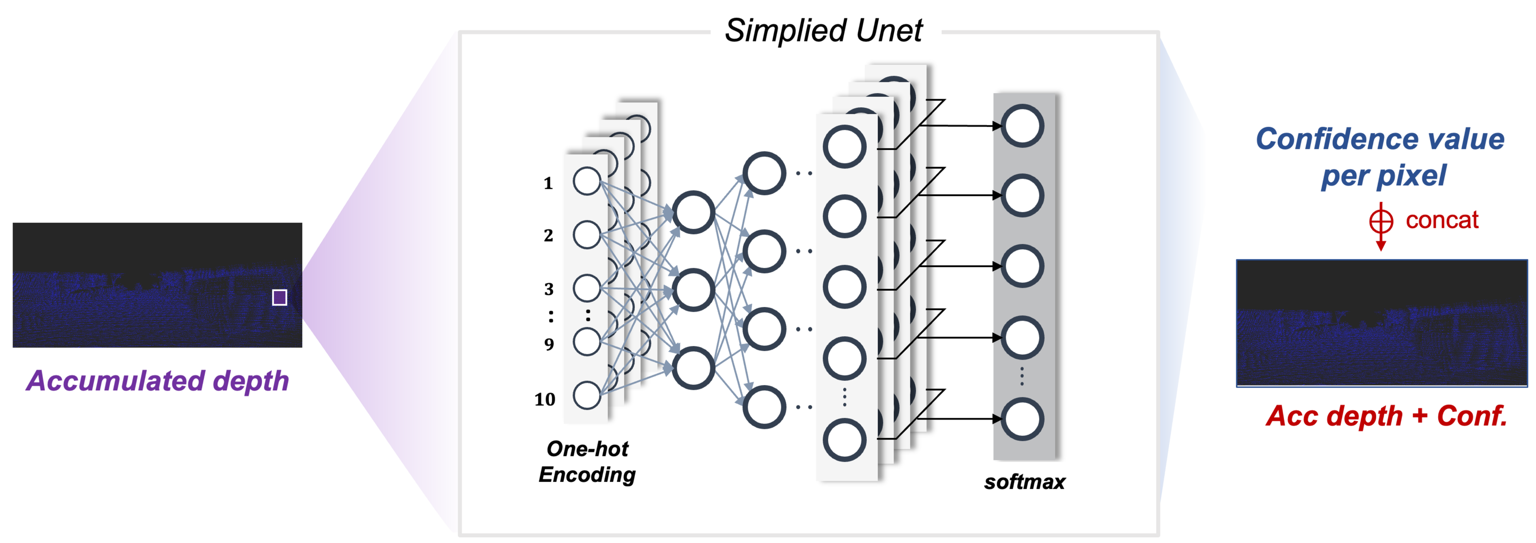
- Projection *'3D pointcloud map'* to '*2D depth map*'



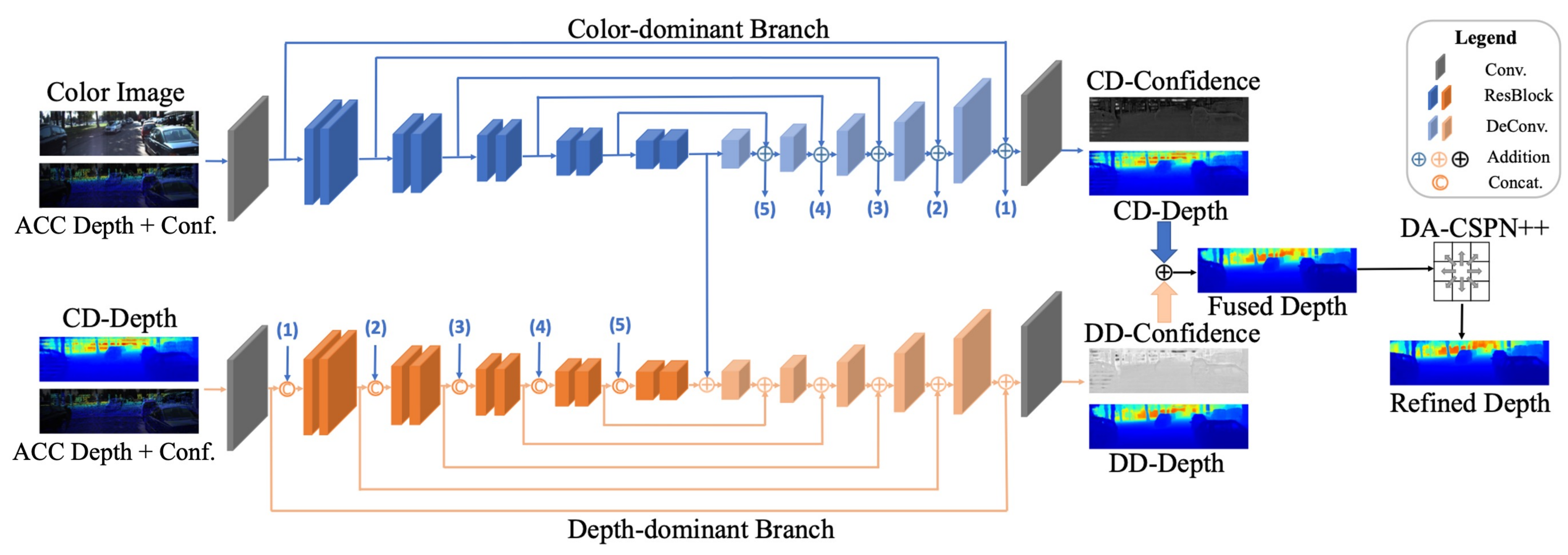
Interference from previous frame on Accumulation

1. *overlapping depth information between the vehicle and wall.*
2. *overlapping depth information of statics against moving objects.*

- **Stage 2** : Denoising Process - *PointCleaner*
  - Designed by simplied *'Unet'* structures (3 Conv + 3 Deconv)
  - One-hot encode each 'frame id difference'
  - Assign confidence values each frame using softmax
  - Concat with accumulated depth and confidence map

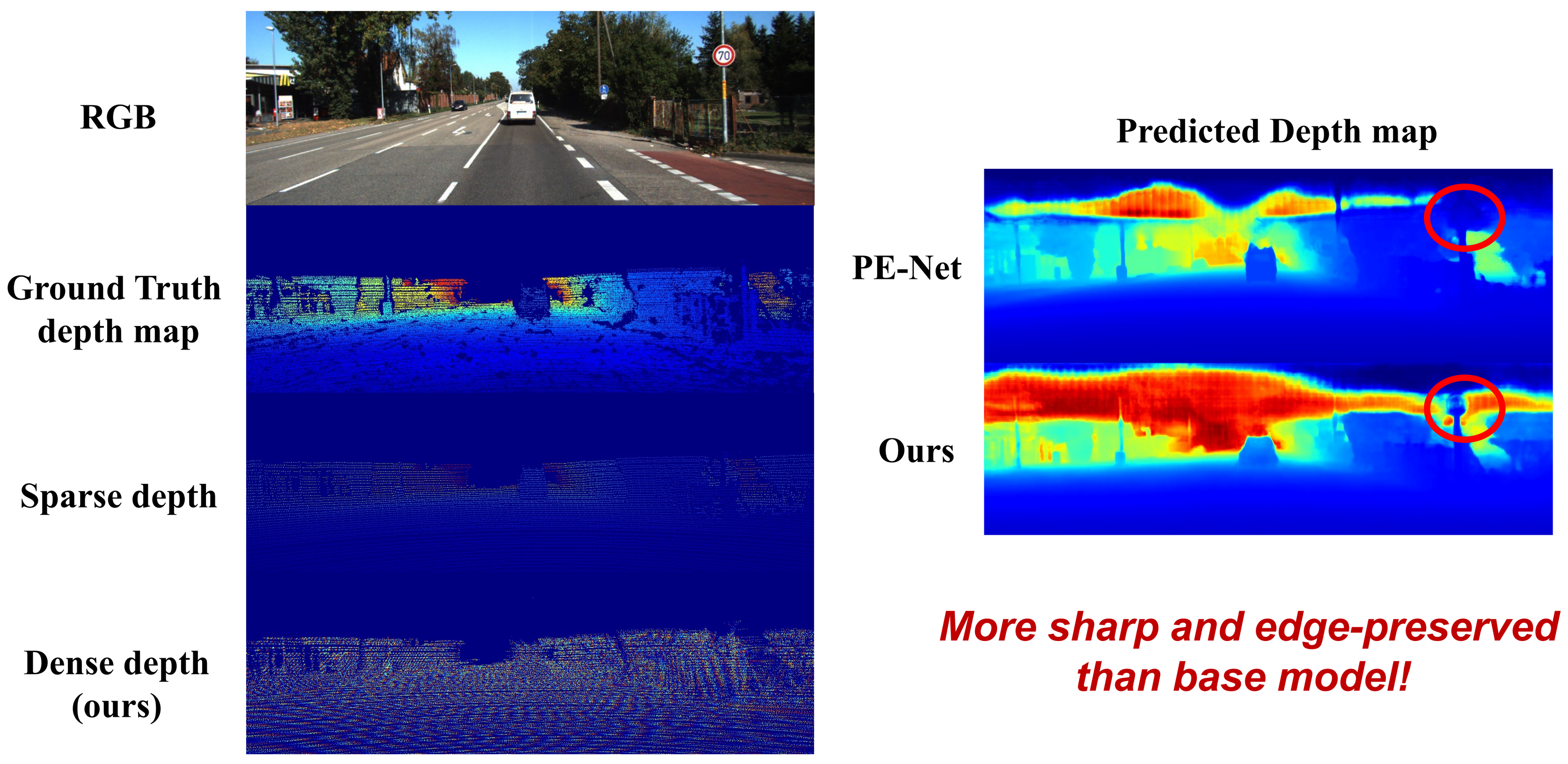


- **Stage 3** : Depth Completion (*PE-Net*)
  - Two-Branch Backbone, fusion with two modalities (Color, Depth)
  - Refine the depth using '*Dilated and Accelerate Convolutional Spatial Propagation Network (DA-CSPN++)*'



Experimental Results

- Training
  - Dataset : KITTI Depth Completion
  - Evaluation Metric : Root Mean Squared Error (mm) = $\sqrt{\frac{1}{|\mathcal{V}|}\sum_{v\in\mathcal{V}}\left|d_v^{gt}-d_v^{pred}\right|^2}$
- Experiments



More sharp and edge-preserved than base model!

Network	RMSE	iRMSE	MAE	iMAE
PE-Net	765.75	1.94	248.89	0.93
Ours (without PointCleaner)	2500.59	10.15	1583.50	7.956
Ours	2220.68	6.69	1198.36	5.68

Conclusion & Future works

- We preprocessing sparse LiDAR raw data to be more densely using SLAM.
- Effectively denoise of accumulated depth with our PointCleaner Network.
- Need to improve performance over base model (*PE-Net*).