Lidar Upsampling with Sliced Wasserstein Distance

Artem Savkin, Yida Wang, Sebastian Wirkert, Nassir Navab, Federico Tombari

KI DELTA LEARNING
Scalable AI for Automated Driving

Sensors

Introduction

Data-driven perception systems require data acquisition and annotation on scale which is an expensive and inflexible process. We address the problem of sensor-to-sensor domain adaptation to avoid re-acquiring or re-annotating the data and focus on the sensor setup with low- and high-resolution lidars and the task of upsampling.

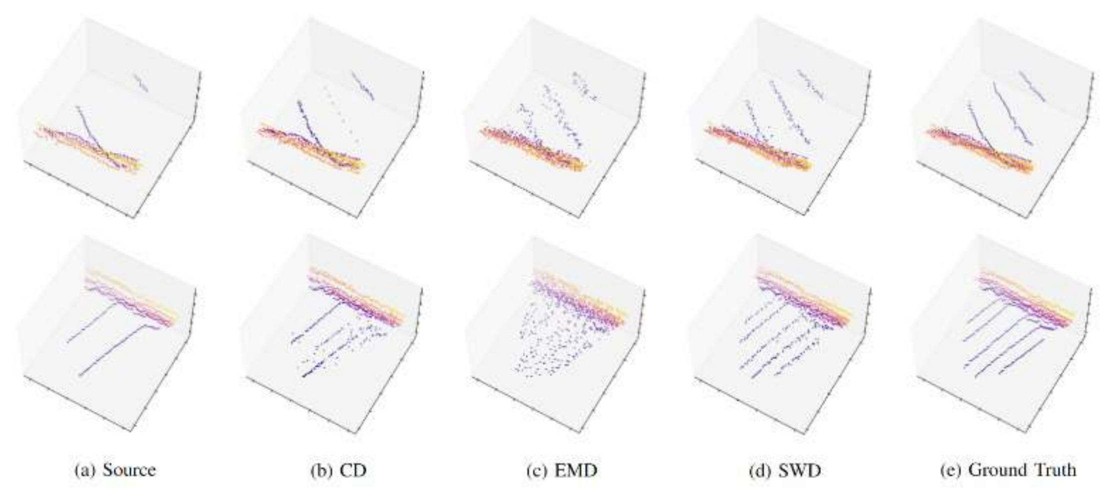

Figure 2: Lidar upsampling using proposed network with conventional loss functions.

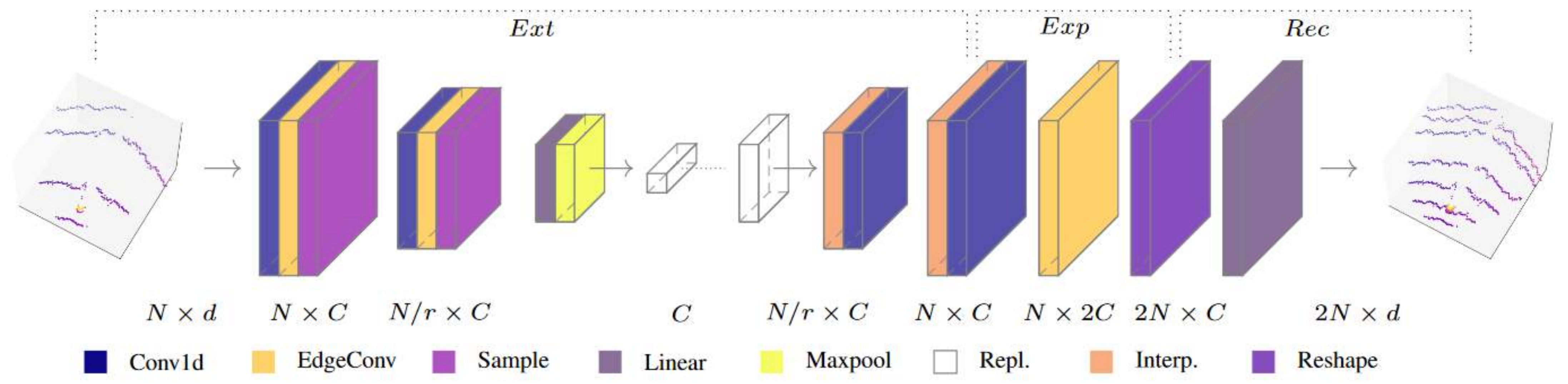

Figure 1: Overview of the network with feature extraction (Ext), feature expansion (Exp) and coordinate reconstruction (Rec)

Approach

The proposed model is built upon upsampling framework with three steps: feature extraction, feature expansion, and coordinate reconstruction. As shown in Figure 1. the feature extractor represents an encoder-decoder and employs dense per-point feature learning with Conv1d and EdgeConv [1] layers. Following the edge-preserving principle, the feature expansion also uses EdgeConv to create N×2C upsampled feature vector. In the final step, a set of linear layers reconstruct the resulting N×3 coordinates.

We propose that higher accuracy of point cloud reconstruction, which is sensitive to fine scan patterns in contrast to Chamfer and Earth Mover's Distances, can be achieved by applying the Sliced Wasserstein (SW) distance as it possesses equivalent statistical properties to WD [4].

Evaluation

Our experiments use KITTI and Waymo datasets. Figure 2. compares traditional losses with SWD for lidar scan reconstruction using PointNetFCAE based on PointNet and a fully connected decoder. Figure 3. compares the upsampling quality of baseline methods PU-Net [2], 3PU [1], PU-GAN[3], and the proposed method on lidar scan patches of 2048 points. The results of upsampling are assessed with traditional metrics: CD, Hausdorff Distance, EMD, and SWD. The assessment presented in Table 1. shows improvement in all metrics except CD.

	CD	HD	EMD	SWD
PU-Net [8]	0.5272	1.2627	0.3851	15.4002
3PU [30]	0.1172	0.4151	0.2740	5.2078
PU-GAN [32]	**0.0426**	0.1892	0.2504	1.3553
Ours	0.0435	**0.1694**	**0.0775**	**1.1742**

Table 1: Quantitative comparison for 2× upsampling of 8192 points on KITTI val dataset.

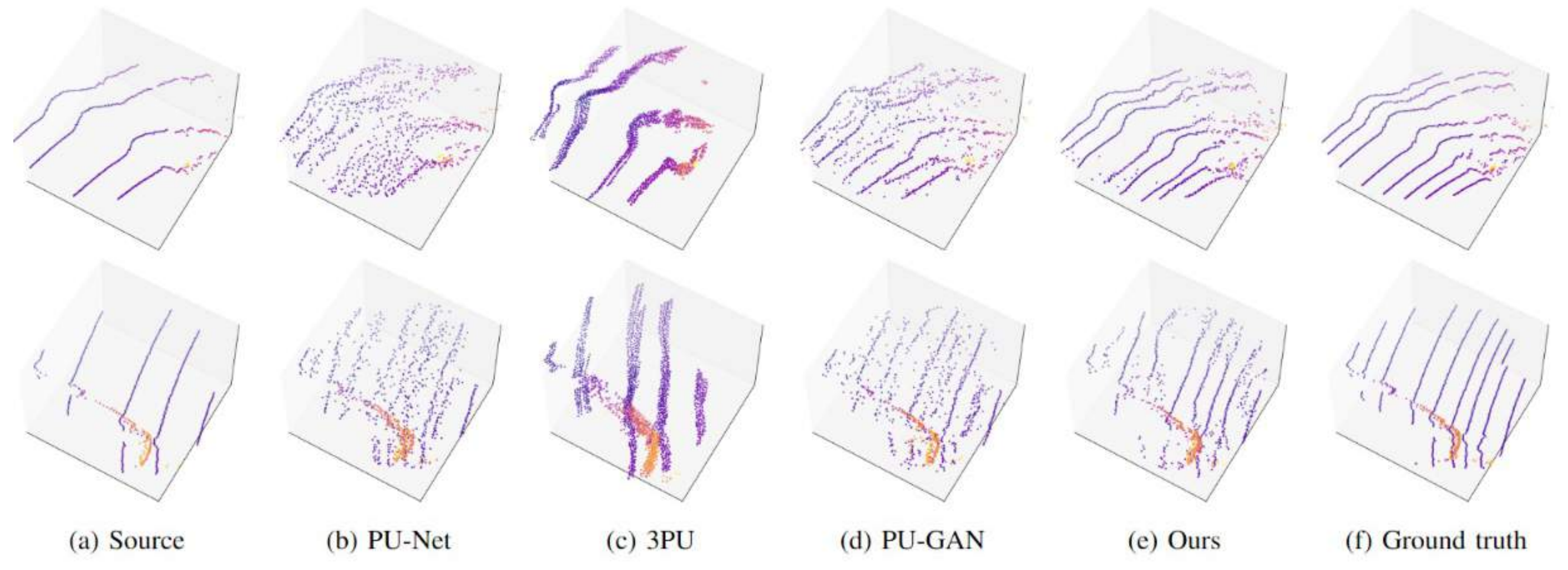

Figure 3. Qualitative comparison of the 2× lidar upsampling results on KITTI test.

References

[1] Y. Wang et al. Patch-Based Progressive 3D Point Set Upsampling. In *CVPR*, 2019.
[2] L. Yu et al. PU-Net: Point Cloud Upsampling Network. In *CVPR*, 2018.
[3] R. Li et al. PU-GAN: a point Cloud Upsamlping Adversarial Network. In ICCV, 2019.
[4] S. Kolouri et al. Sliced-Wasserstein Auto-Encoders. In ICLR, 2017

Partners

External partners

For more information contact:
artem.savkin@bmw.de
sebastian.wa.wirkert@bmw.de

KI Delta Learning is a project of the KI Familie. It was initiated and developed by the VDA Leitinitiative autonomous and connected driving and is funded by the Federal Ministry for Economic Affairs and Climate Action.

Supported by: Federal Ministry for Economic Affairs and Climate Action

on the basis of a decision by the German Bundestag

KI FAMILIE

www.ki-deltalearning.de @KI_Familie KI Familie