Background Search

Digital Image Processing

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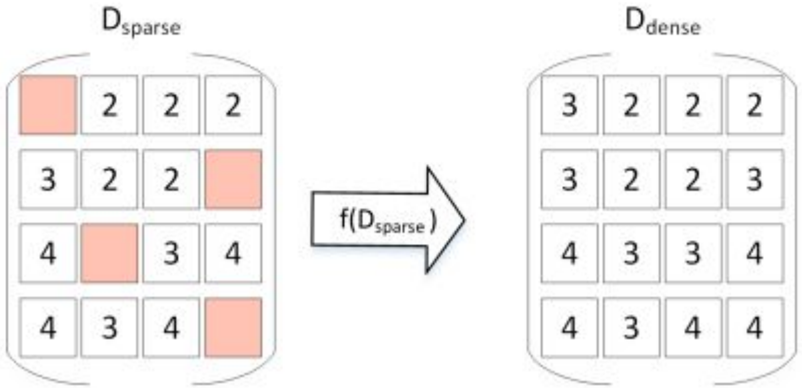
Summary

1. In Defense of Classical Image Processing: Fast Depth Completion on the CPU
2. Journals
    - A comparative review of plausible hole filling strategies in the context of scene depth image completion
    - A survey on deep learning techniques for stereo-based depth estimation
    - Depth map artefacts reduction: a review
3. Conferences
    - Depth completion from sparse lidar data with depth normal constraints
    - Self-Supervised Sparse-to-Dense: Self-Supervised Depth Completion from LiDAR and Monocular Camera
    - LIDAR and Monocular Camera Fusion: On-road Depth Completion for Autonomous Driving
    - Deep Adaptive LiDAR: End-to-end Optimization of Sampling and Depth Completion at Low Sampling Rates
    - UAMD-Net: A Unified Adaptive Multimodal Neural Network for Dense Depth Completion
    - Radar-Camera Pixel Depth Association for Depth Completion
    - Depth Completion via Inductive Fusion of Planar LIDAR and Monocular Camera
    - From Depth What Can You See? Depth Completion via Auxiliary Image Reconstruction
    - Grayscale And Normal Guided Depth Completion With A Low-Cost Lidar
    - Sparsity Invariant CNNs
4. Benchmarking

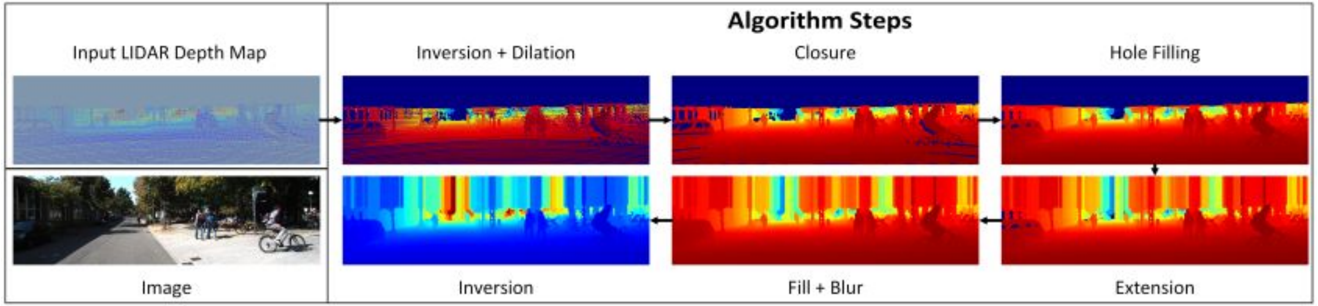
In Defense of Classical Image Processing: Fast Depth Completion on the CPU

- Paper on which our work is based
- Well designed classical algorithms are capable of outperforming neural network
- Depth completion
- Non-guided
- LIDAR data



Proposed Algorithm

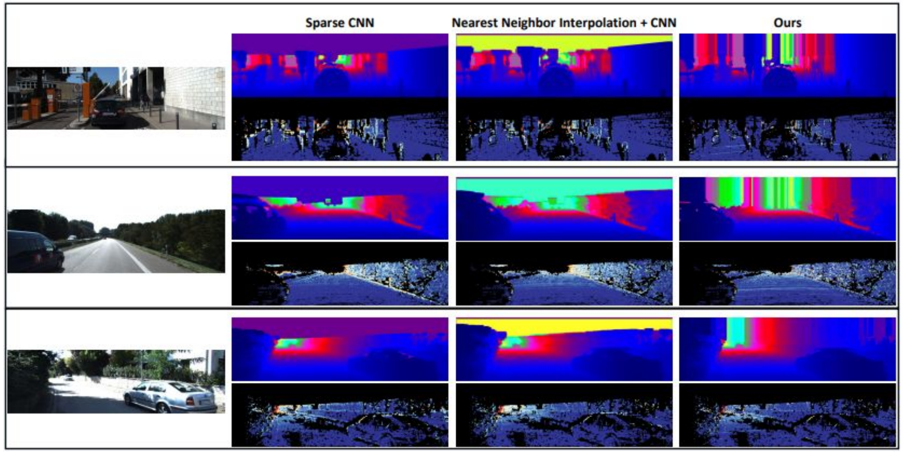
1) Depth Inversion
2) Custom Kernel Dilation
3) Small Hole Closure
4) Small Hole Fill
5) Extension to Top of Frame
6) Large Hole Fill
7) Median and Gaussian Blur
8) Depth Inversion



Results

Method	iRMSE (1/km)	iMAE (1/km)
NadarayaW	6.34	1.84
SparseConvs	4.94	1.78
NN+CNN	**3.25**	**1.29**
Ours (IP-Basic)	3.78	**1.29**

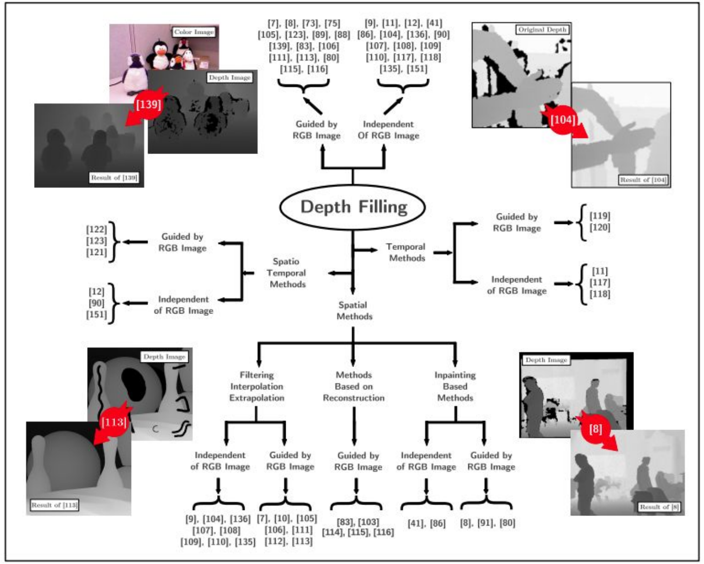
Method	RMSE (mm)	MAE (mm)	Runtime (s)
NadarayaW	1852.60	416.77	0.05
SparseConvs	1601.33	481.27	**0.01**
NN+CNN	1419.75	416.14	0.02
Ours (IP-Basic)	**1288.46**	**302.60**	0.011



JOURNALS

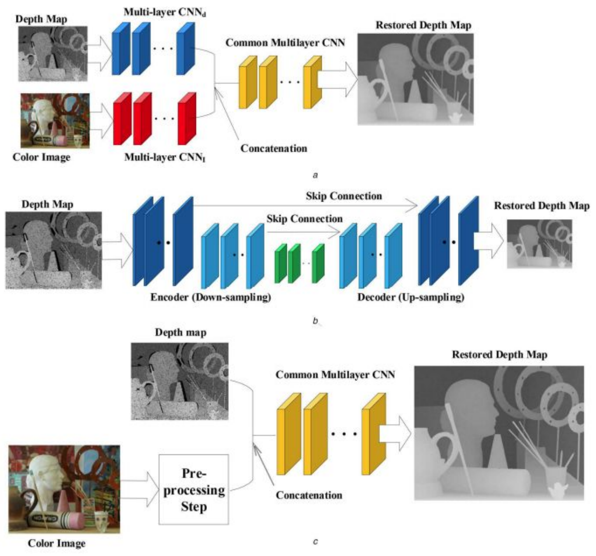
A comparative review of plausible hole filling strategies in the context of scene depth image completion

- Survey that provide a state of the art overview the field of depth synthesis
- Good depth maps are crucial for most 3D detection methods
- Classical image processing



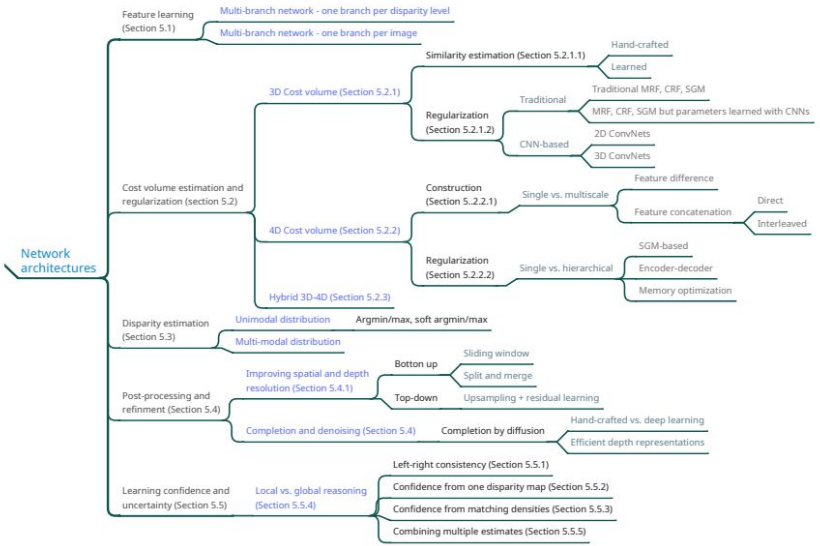
Depth map artefacts reduction: a review

- Survey about depth map artefacts reduction methods proposed in the literature
- Depth maps are very important for a big variety of a visual applications
- CNN for depth completion in LIDAR data
- RNN are still not exploited



A Survey on Deep Learning Techniques for Stereo-based Depth Estimation

- Deep learning survey for depth estimation based on stereo images
- Classical imagem processing methods suffer from problems
- Deep learning approach drawing attention from the community
- Convolutional Spatial Propagation Networks (CSPN)



CONFERENCES

Sparsity Invariant CNNs (30 Aug 2017)

- Convolutional Neural Networks
- Sparse convolution layer
- Comparisons, Experiments and results

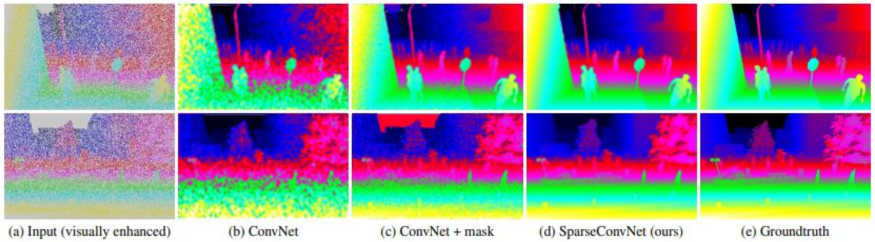
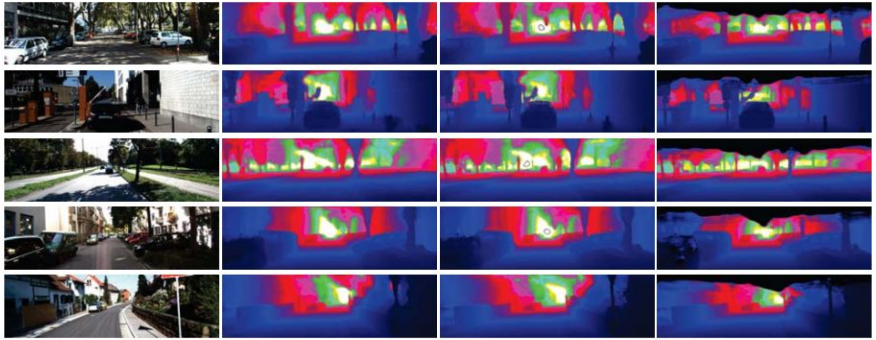


Figure 5: Qualitative comparison of our sparse convolutional network to standard ConvNets on Synthia [54], trained and evaluated at 5% sparsity. (b) Standard ConvNets suffer from large invalid regions in the input leading to noisy results. (c) Using a valid mask as input reduces noise slightly. (d) In contrast, our approach predicts smooth and accurate outputs.

Self-Supervised Sparse-to-Dense: Self-Supervised Depth Completion from LiDAR and Monocular Camera (20-24 May 2019)

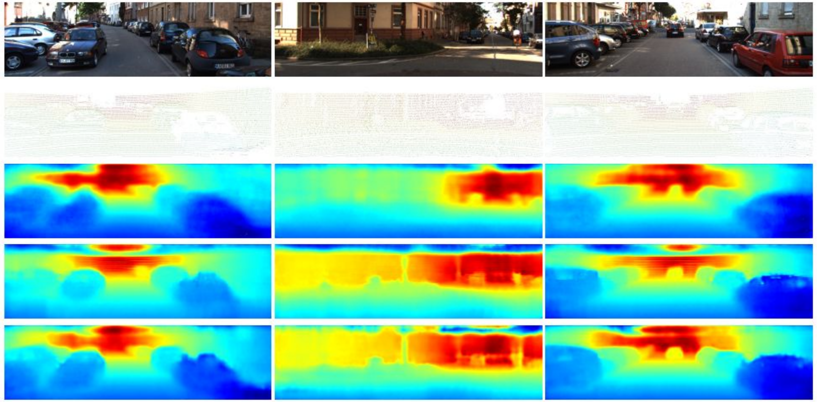
- Three Main depth completion challenges
- Self-supervised training framework
- Experiments and results



(a) RGB (b) Photometric Only (c) Self-supervised (d) Supervised

LIDAR and Monocular Camera Fusion: On-road Depth Completion for Autonomous Driving (27-30 Oct. 2019)

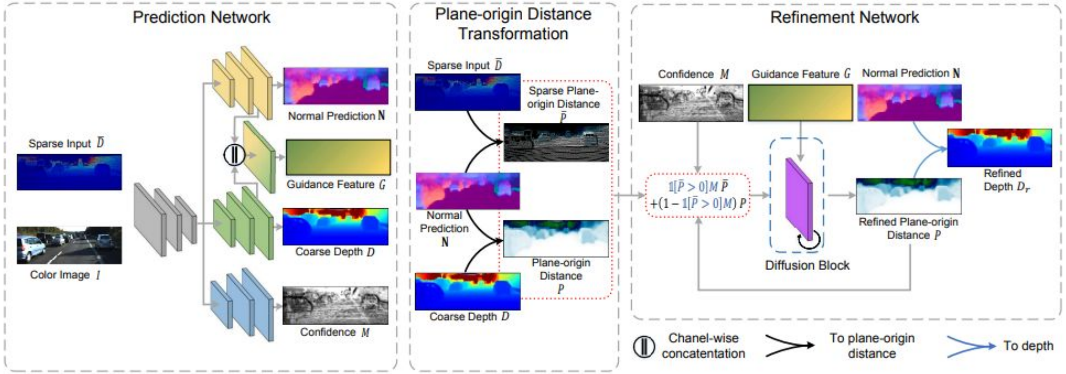
- LIDAR and RGB cameras
- Technologies fusion
- Experiments and results



(a) Scene 1 (b) Scene 2 (c) Scene 3

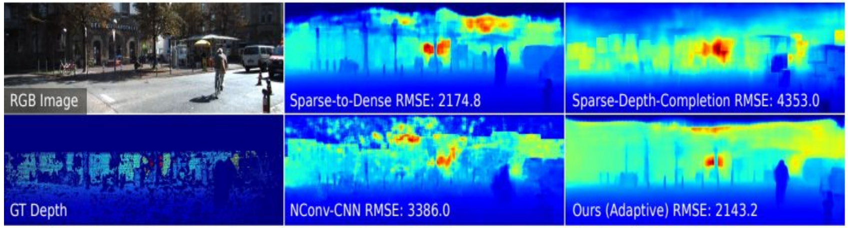
Depth completion from sparse lidar data with depth normal constraints (27 Oct. 2019 – 2 Nov. 2019)

- Current competitive methods
- Unified CNN framework
- Experiments and Results



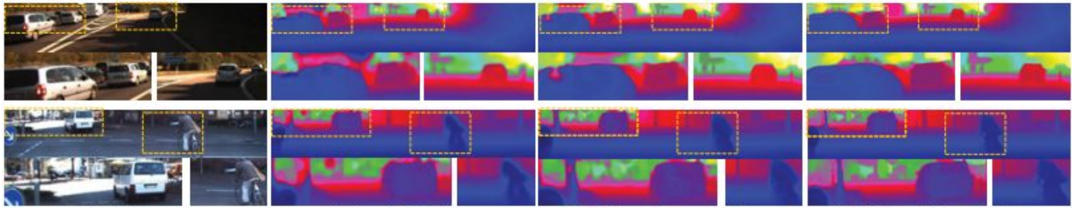
Deep Adaptive LiDAR: End-to-end Optimization of Sampling and Depth Completion at Low Sampling Rates (24-26 April 2020)

- Current LIDAR and DP problem
- Adaptative LIDAR and results



From Depth What Can You See? Depth Completion via Auxiliary Image Reconstruction (14 – 19 Jun. 2020)

- Existing depth-only methods
- Unique design
- Experiment and results

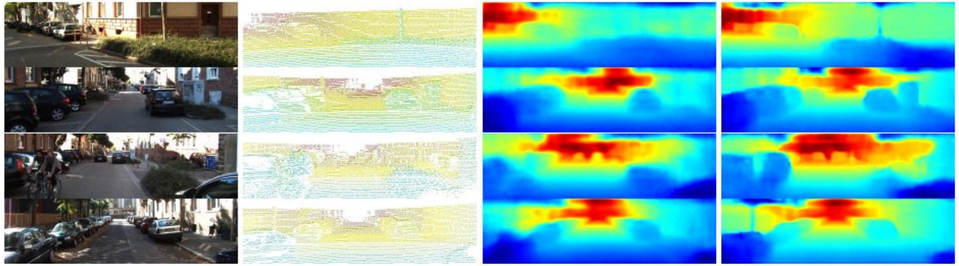


(a) RGB image (b) Only with depth features (c) With image features w/o sharing (d) With image features and sharing

Figure 7. Visual comparison of depth completion results after incorporating image reconstruction and feature sharing. (a) RGB images for reference. (b) Only with depth features cannot recover the full structure of objects. (c) With image features but without sharing, the results are slightly improved. (d) With shared features, the model performs better in recovering consistent object structures and small/thin objects.

Depth Completion via Inductive Fusion of Planar LIDAR and Monocular Camera (24 Oct.-24 Jan. 2021)

- Modern HD LIDAR
- Inductive late-fusion block
- Experiment and results



(a) RGB image (b) Ground Truth (c) [4] (d) Proposed

Fig. 6: Visualization result on KITTI dataset on official validation sets. The images from left to right are: RGB image, ground truth dense depth (brightness, contrast changed for visual enhancement), predicted dense depth image from previous work [4] and prediction dense depth image by proposed method. We are using 200 depth points in this experiment setting.

Radar-Camera Pixel Depth Association for Depth Completion (19 – 25 Jun. 2021)

- Radar and video fusion
- Radar-to-pixel association
- Experiment and results

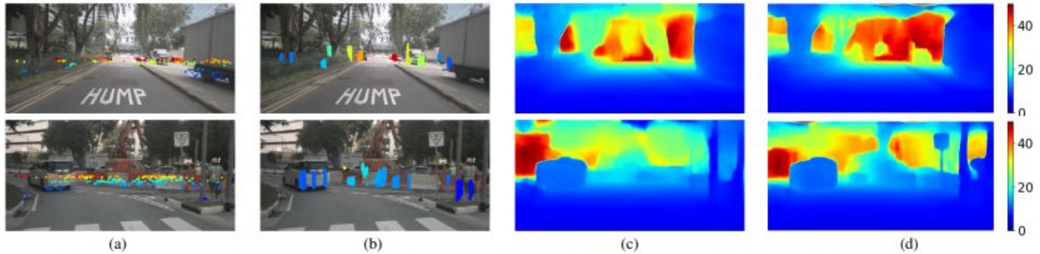
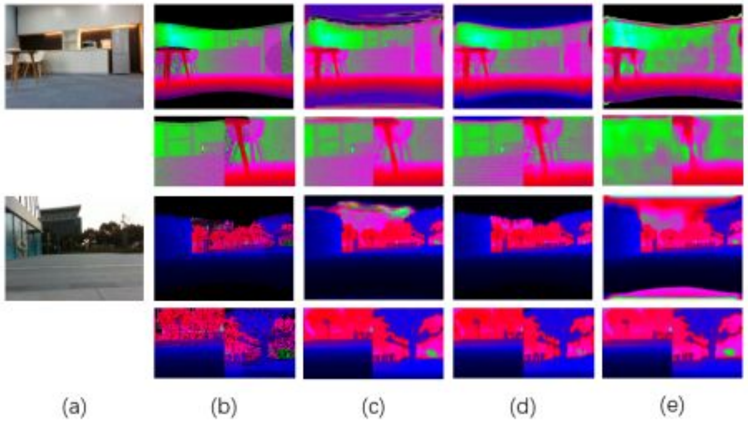


Figure 12: Qualitative depth completion comparison showing gains from using MER over raw radar. (a) Raw radar on top of image versus (b) A MER channel with RC-PDA > 0.8 on top of image. Depth completion (c) without and (d) with using MER.

Grayscale And Normal Guided Depth Completion With A Low-Cost Lidar (19-22 Sept. 2021)

- DenseLivox
- Multi-task learning network
- Comparisons, experiments and results



UAMD-Net: A Unified Adaptive Multimodal Neural Network for Dense Depth Completion (16 Apr. 2022)

- Depth prediction problem
- UAMD-Net
- Comparisons, experiment and results

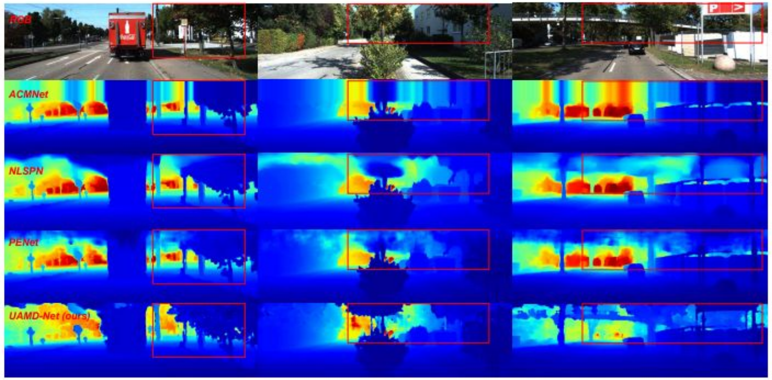


Figure 4. Qualitative results of different methods. From top to down are the input images, results of ACMNet [25], NLSPN [16], PENet [11] and our UAMD-Net respectively.

Benchmarking

Dynamic Spatial Propagation Network for Depth Completion

- SPN Networks and Depth completion
- Affinity among neighbor pixels
- DS operation

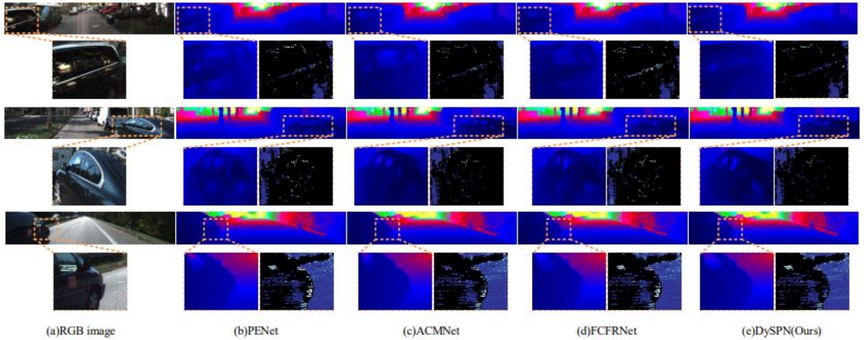


Figure 5: Qualitative comparisons results with other methods on KITTI DC evaluation. (b) PENet (Hu et al. 2021), (c) ACMNet (Zhao et al. 2021), (d) FCFRNet (Liu et al. 2021).

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