

Super sampling of 3D scans using deep learning

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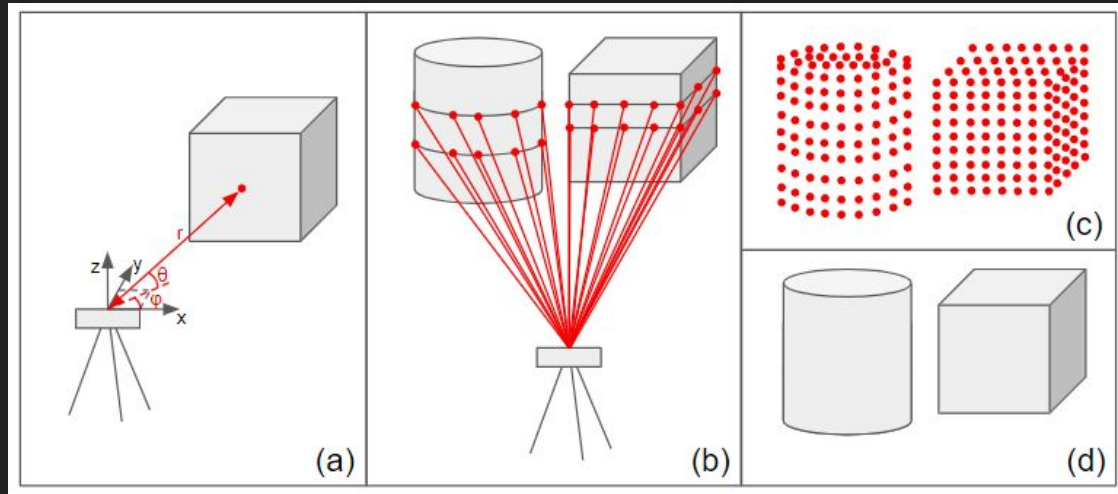
3D scanning

- Virtual representation of 3D objects
- Usage: product validation, analysis of archeological findings...



Representation of scanned scene

- Point cloud - set of points in 3D space
- Structured point cloud - 2D matrix where every element represents information about position in 3D space



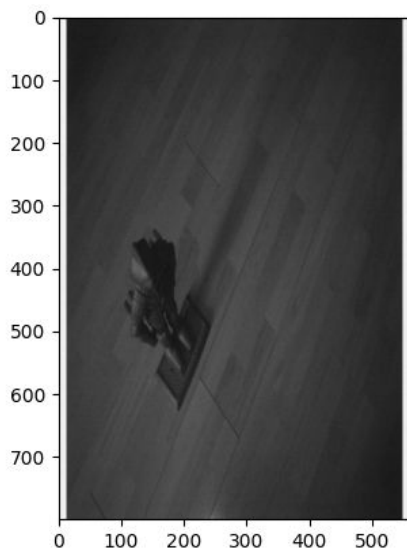
Data from MotionCam-3D

- Depth map (Structured point cloud)
- Intensity texture (Grayscale photo)

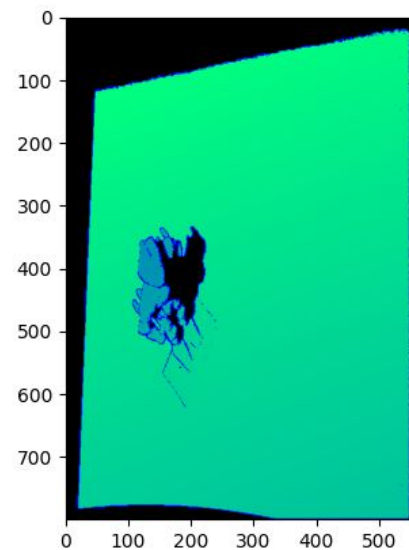


Photoneo MotionCam-3D

MotionCam-3D data example



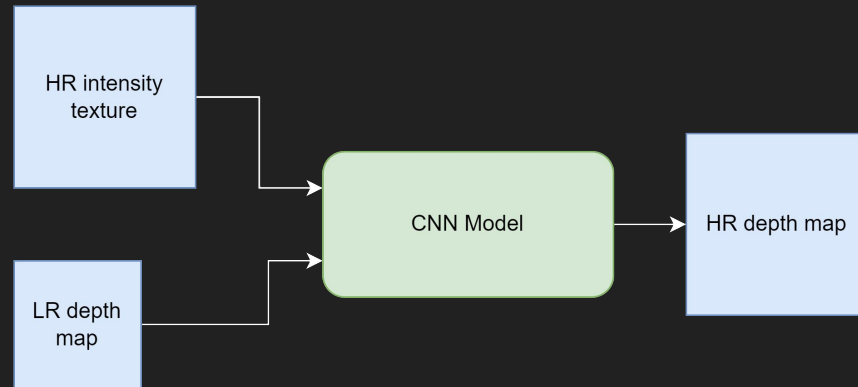
Grayscale



Linear scale **blue** to **green**

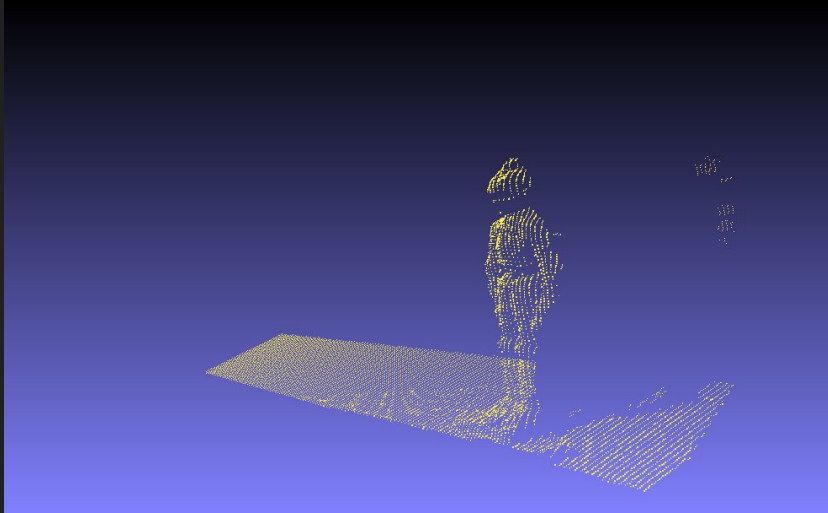
Problem definition

- Depth map super resolution
- INPUT: LR depth map, HR Intensity texture (grayscale image)
- OUTPUT: HR depth map
- Intensity texture is used as guidance image (additional input information)

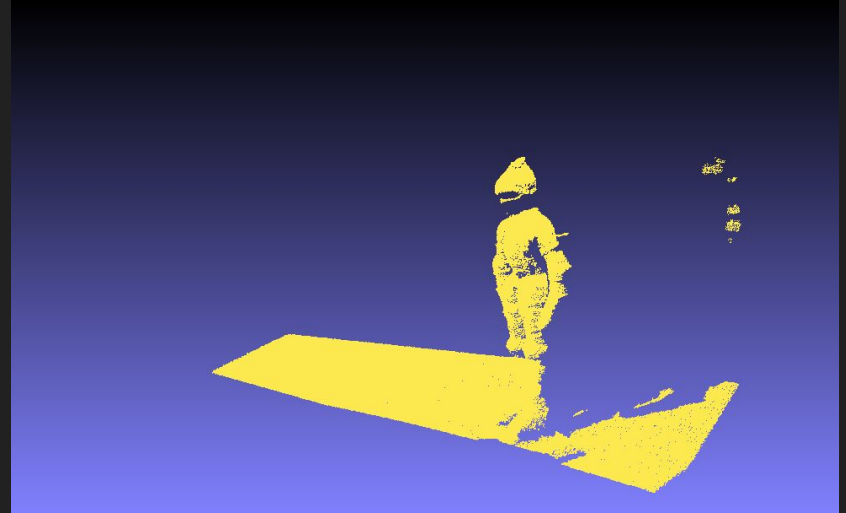


Problem definition

- Point clouds generated from LR and HR depth maps



LR



HR

Goals of thesis

- Create dataset using Photoneo MotionCam-3D
- Choose and implement CNN model for defined problem
- Propose metric for evaluation

Dataset

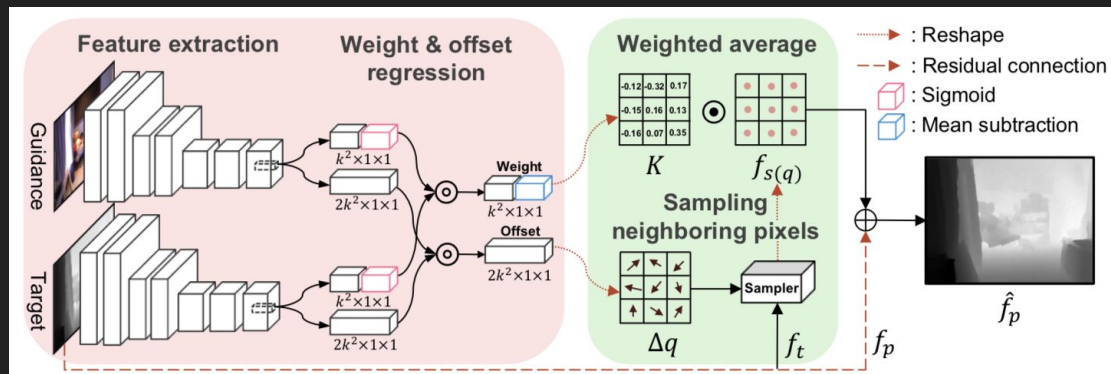
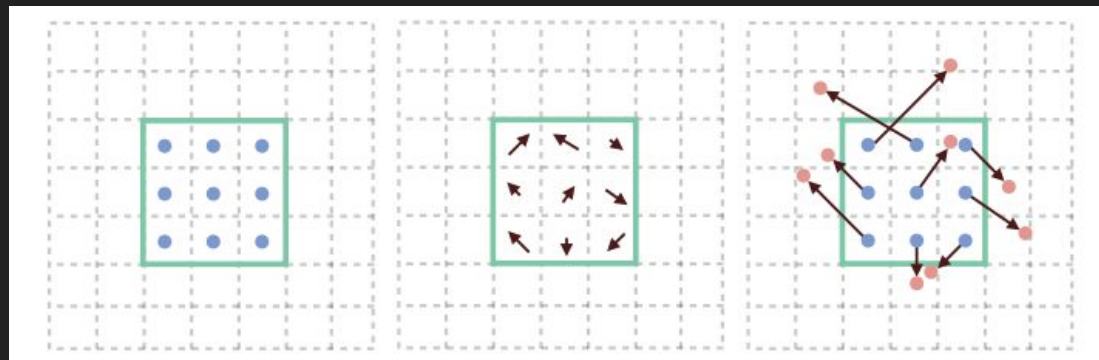
- Dataset sample is triplet: HR intensity texture, LR depth map, HR depth map
- Dataset size: 1200 samples
- Main focus on the 3D object fusion task
- Scene type: One object placed on the flat ground surface



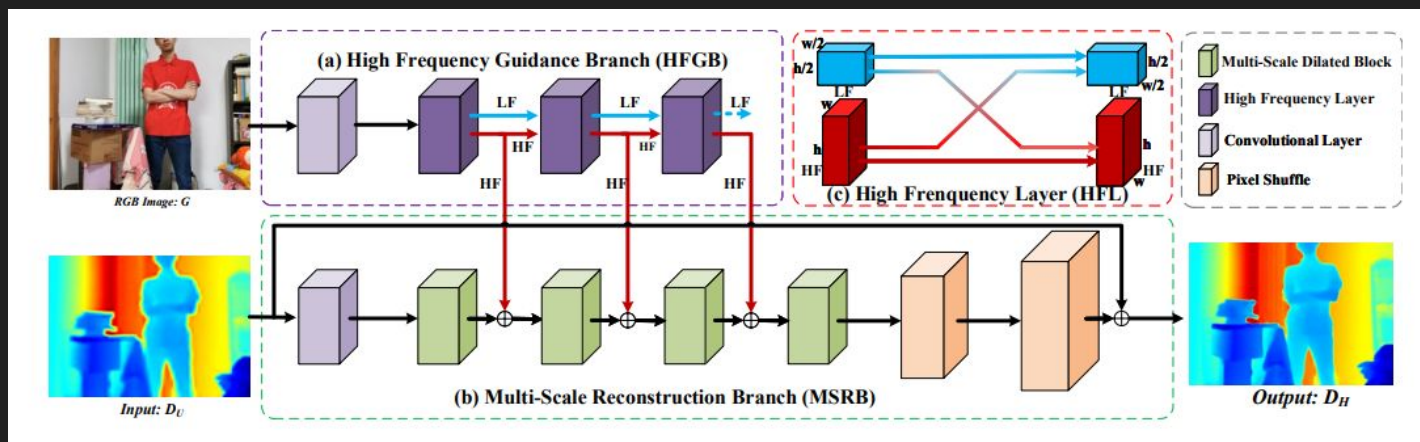
Implemented Depth map SR models

- **FDSR** : *Towards Fast and Accurate Real-World Depth Super-Resolution: Benchmark Dataset and Baseline, Lingzhi He et al. 2021*
- **DKN** : *Deformable Kernel Networks for Joint Image Filtering: Beomjun Kim, Jean Ponce, Bumsub Ham 2019*

DKN model architecture

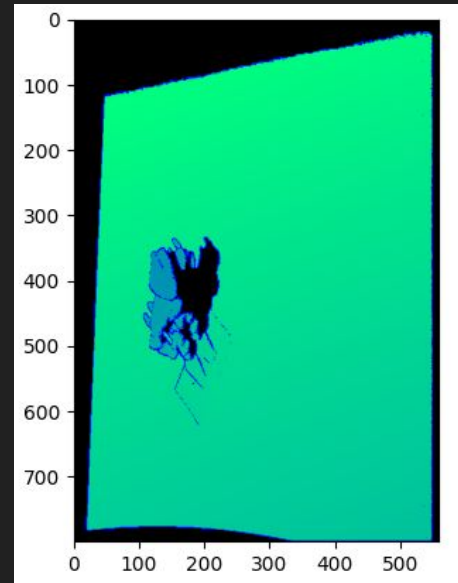


FDSR model architecture



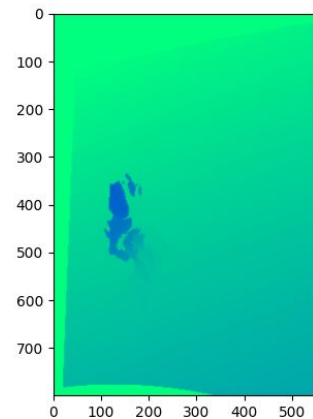
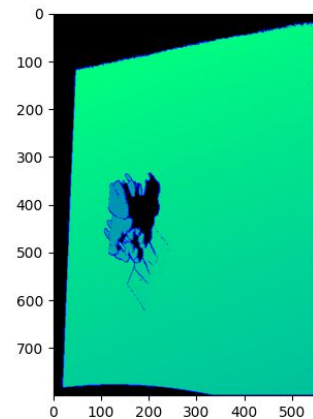
Undefined areas in depth maps

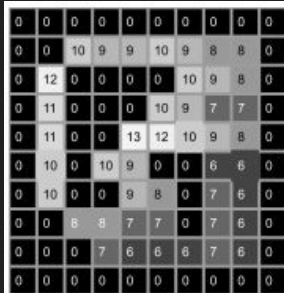
- Depth maps contain undefined pixels that form areas (Black pixels)
- Existing models work with filled depth maps
- *Hole-Filling of RealSense Depth Images Using a Color Edge Map, Ji-Min Cho, Soon-Yong Park, Sung-Il Chien 2020*



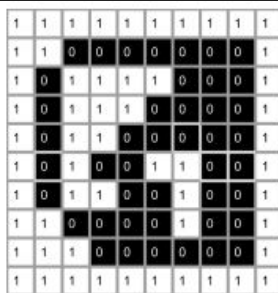
Filling depth maps

- We propose filling method that:
 - Separates object from background
 - Fills background
 - Fills small near object holes
- We have to care about undefined pixels while training otherwise they create large error

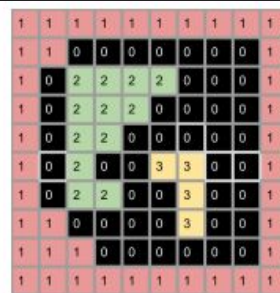




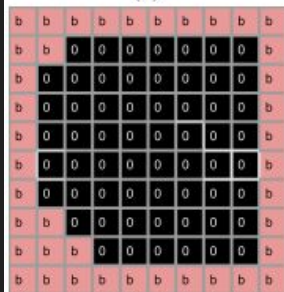
(a)



(b)



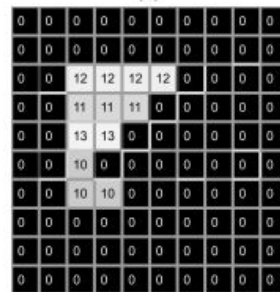
(c)



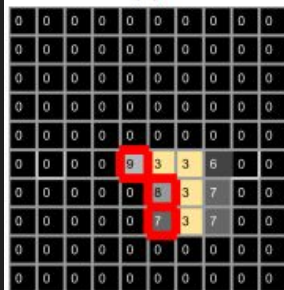
(d)



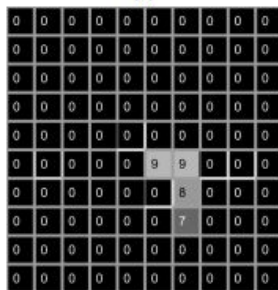
(e)



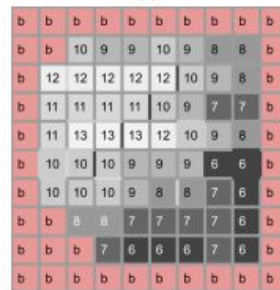
(f)



(g)



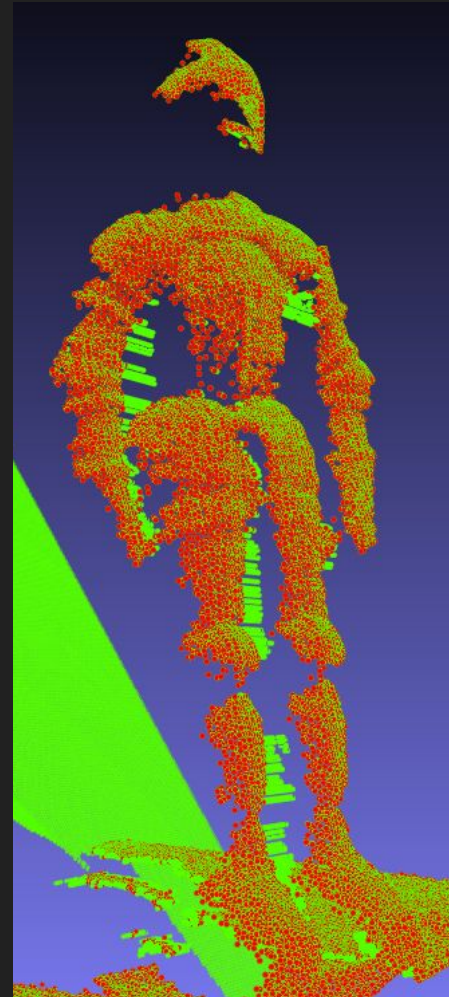
(h)



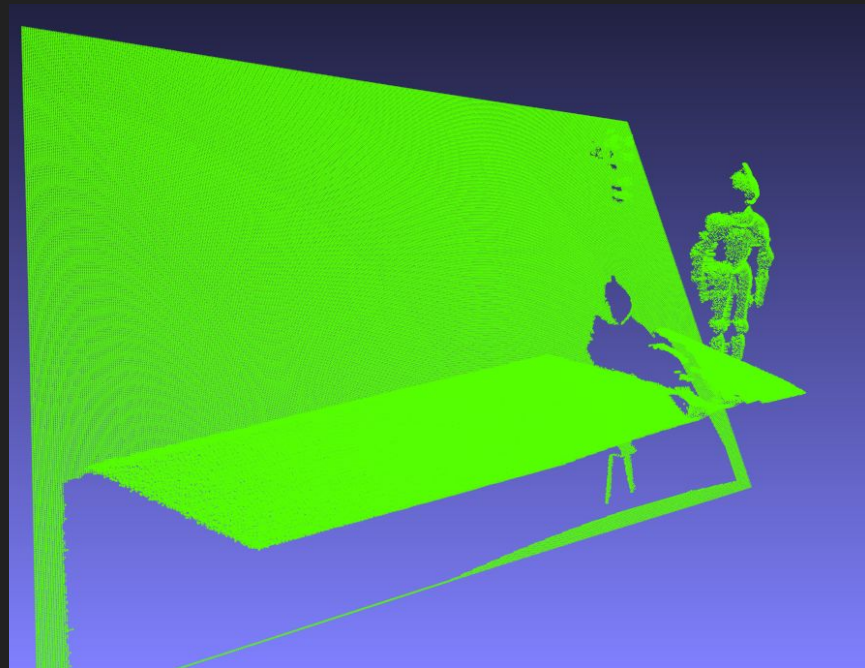
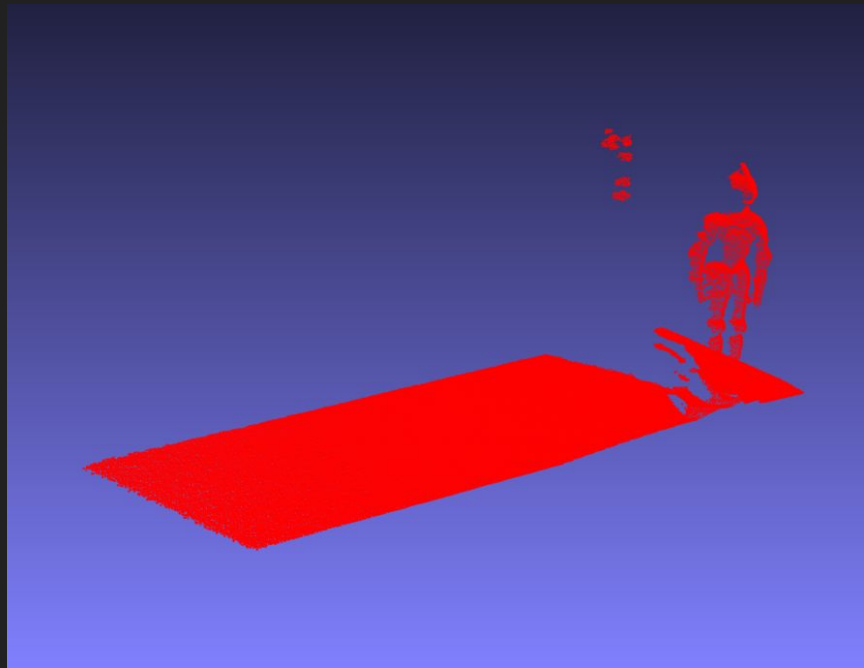
(i)

Depth map filling

- Small holes filled row-wise
- Hole row filled with maximum value of the row's hole border pixels
- Approximate reasonable values for stable training

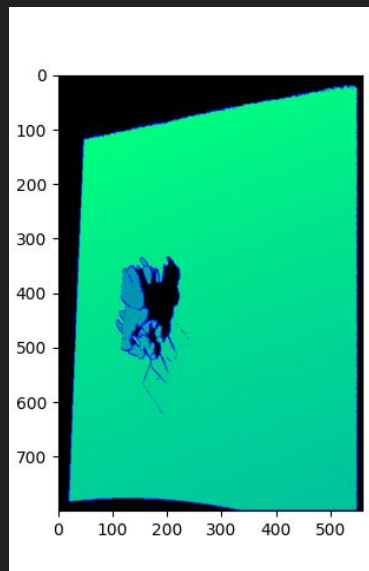
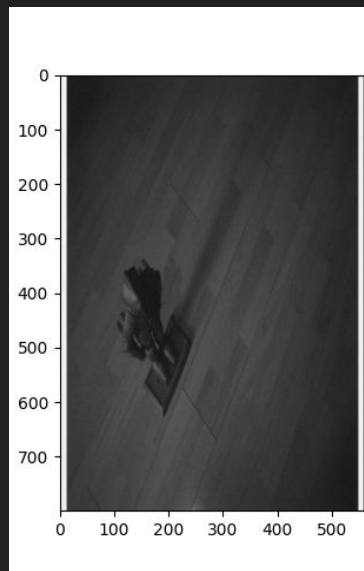


Depth map filling - background plane



Texture augmentation

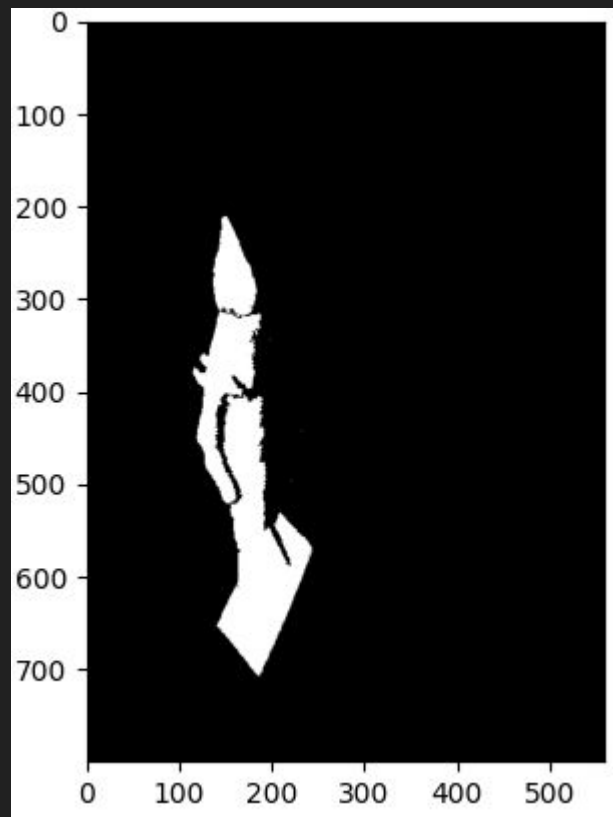
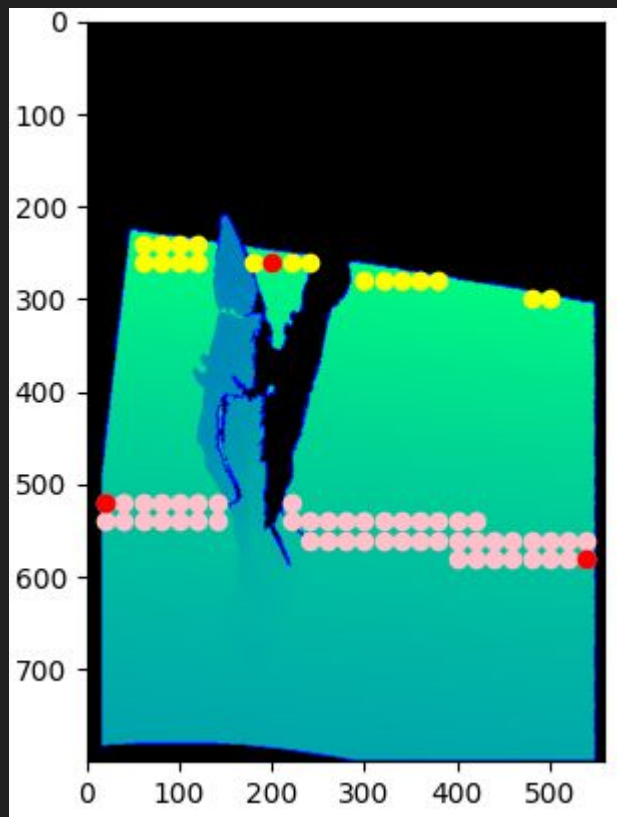
- Improve correlation between depth map and intensity texture
- Apply same filling procedure as for depth map undefined areas
- Removes surface structures from undefined areas



Modifying CNN models

- Halving DKN filters on each layer to fit our hardware limitations
- FDSR and DKN use L2 loss
- We propose loss function that gives attention to scanned object
- Object loss function:
 - Fitting plane to scene ground
 - Extracting set of pixels representing scanned object
 - Assign 100-times higher weight to the object's pixels
 - Compute weighted mean squared error

Object loss function



Evaluation

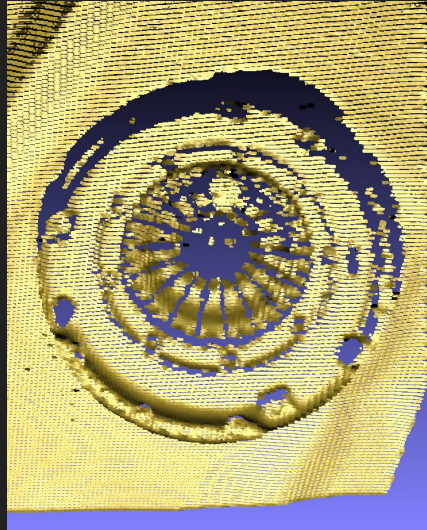
- Metrics
 - Depth map - RMSE (quantitative)
 - Point cloud
 - Analysis in Meshlab (qualitative)
 - Hausdorff's distance of point clouds (quantitative)
 - Mesh - future work

Depth map metric -RMSE

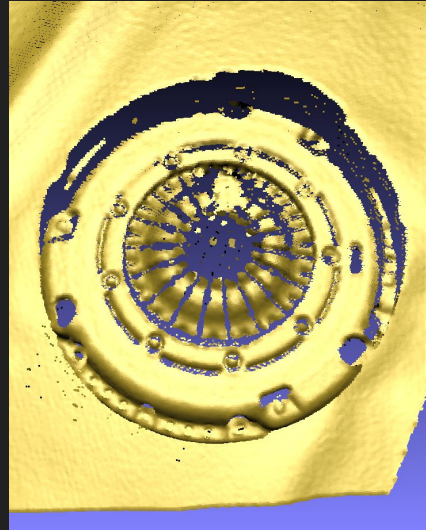
- RMSE - Root mean squared error
- Object RMSE - RMSE computed only from object's pixels
- Object loss - Our proposed loss function

Method	RMSE	Object RMSE	Object loss
FDSR	1.9537	4.4297	1.0427
DKN	2.2696	6.9191	2.3058
Nearest	3.0778	10.8156	7.0692

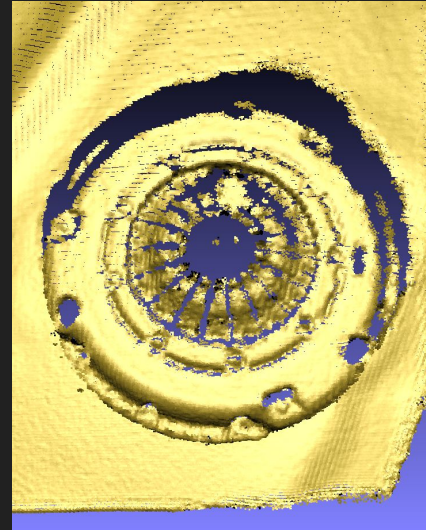
Point cloud metrics - Meshlab analysis



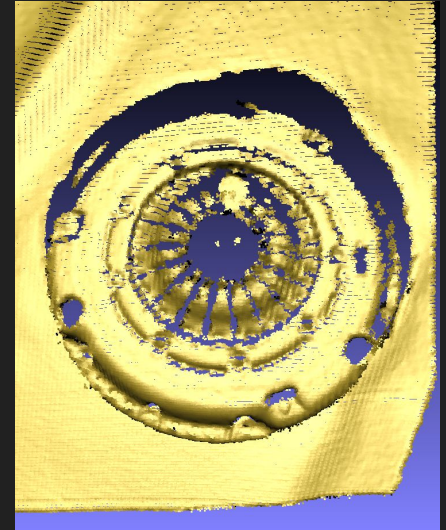
LR



HR



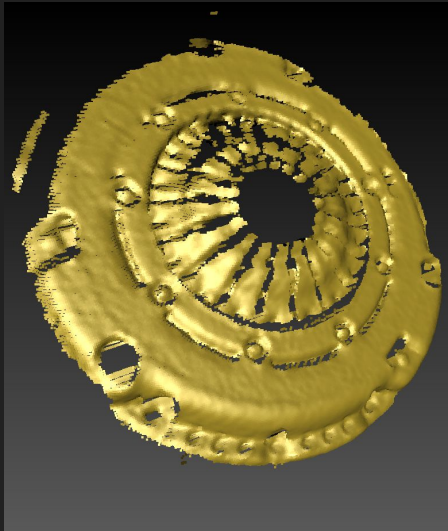
DKN



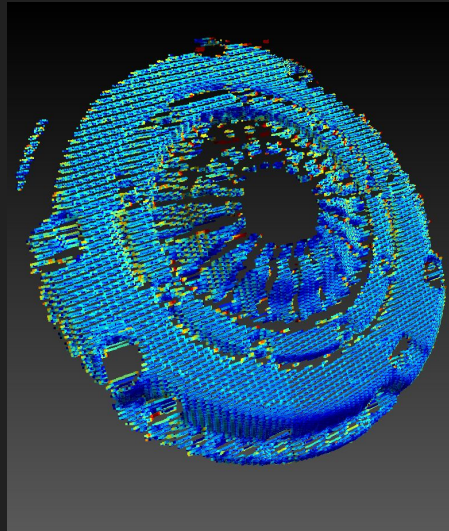
FDSR

Point cloud metrics - Hausdorff's distance

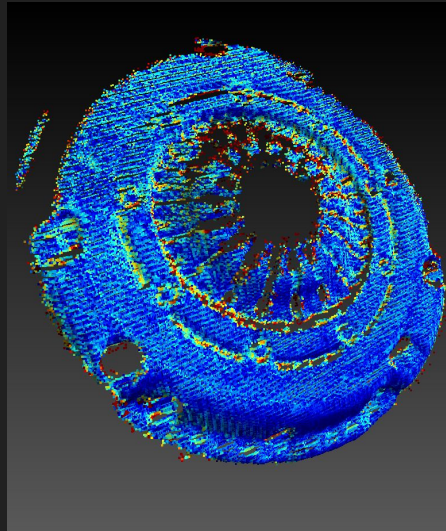
- Linear mapping of Hausdorff's distance to RGB spectre
- Mapping is from **blue** (small distance) through **green** to **red** (large distance) scale 0 - 2 mm



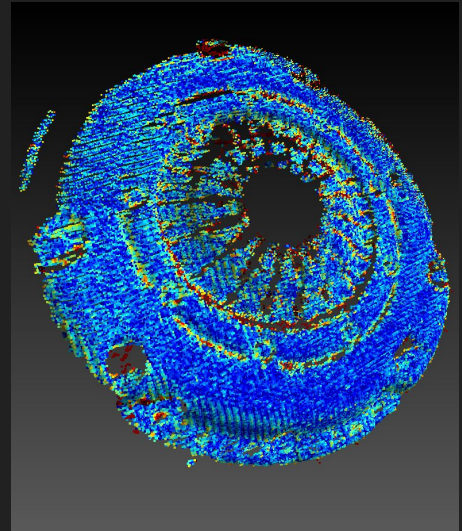
HR



LR



DKN



FDSR

Point cloud metrics - Hausdorff's distance

Method	min	max	mean	RMSE
FDSR	0.0000	9.8178	0.4650	0.7755
DKN	0.0000	10.3815	0.4449	0.7978
Nearest	0.0000	29.5586	0.4144	0.7455

Time measurements

- Pipeline computing time

Resolution [px]	140x200	560x800	1120x800	1680x1200
Time [s]	0.054	0.068	0.091	0.184

- Models computing time

Model	FDSR	DKN
Time [s]	0.007	0.634

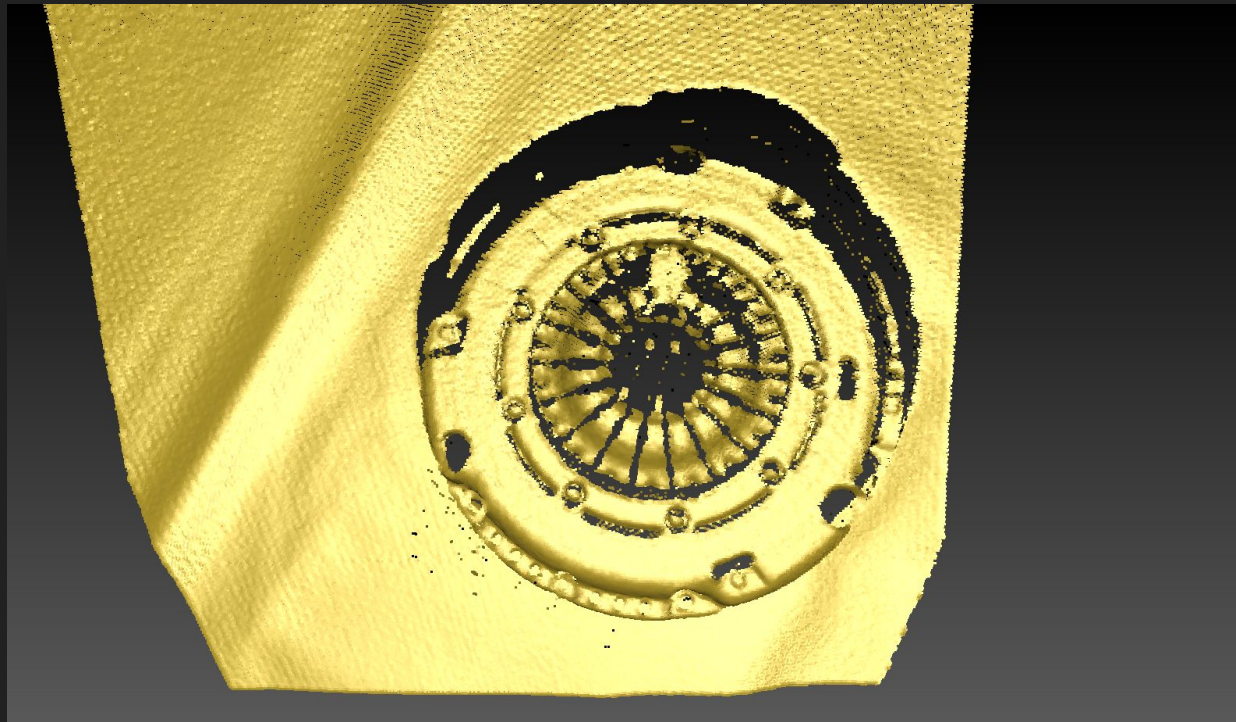
Thank you for your attention

Martin Melicherčík

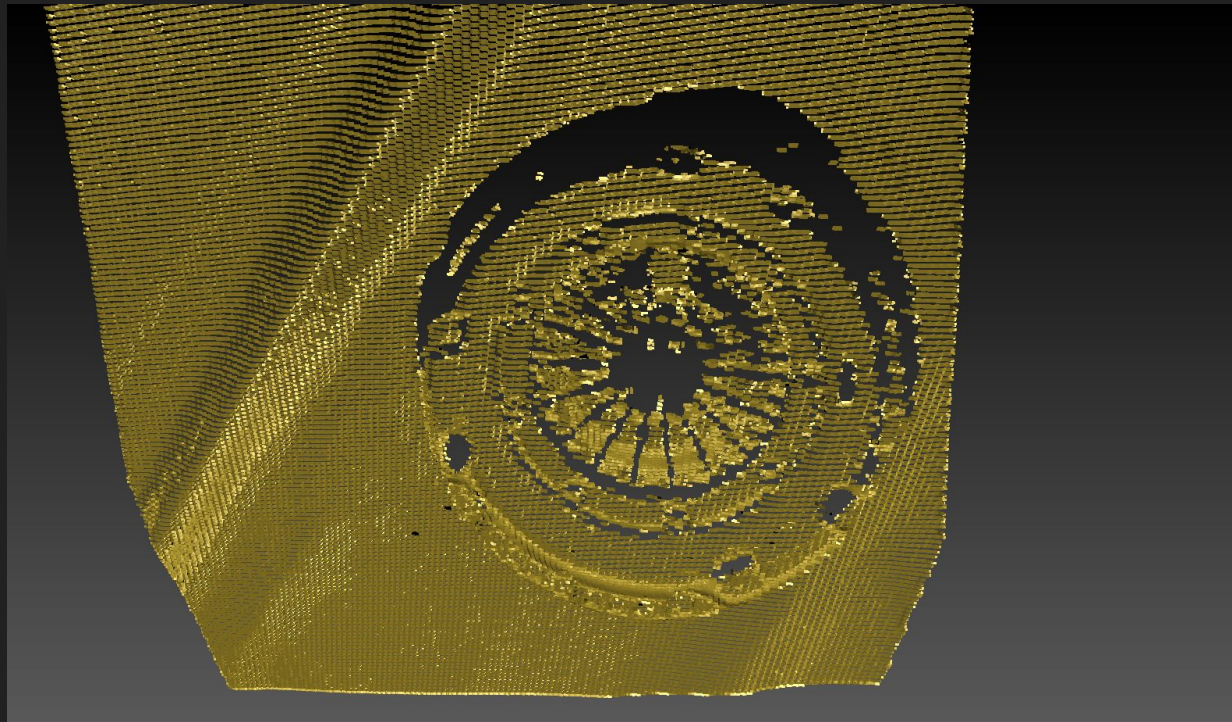
Downsampling vs. Upsampling time

Operation	FDSR Upsampling	DKN Upsampling	Downsampling
Time [s]	0.007	0.634	1.68

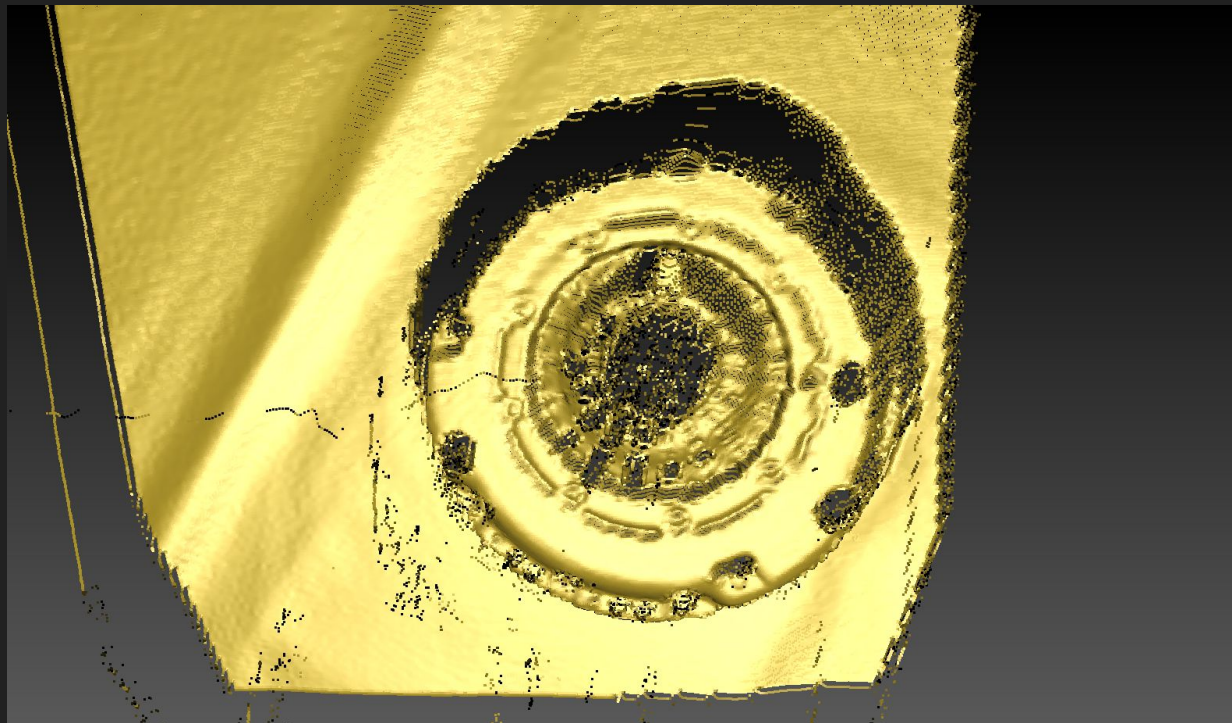
HR



LR - NEAREST NEIGHBOR



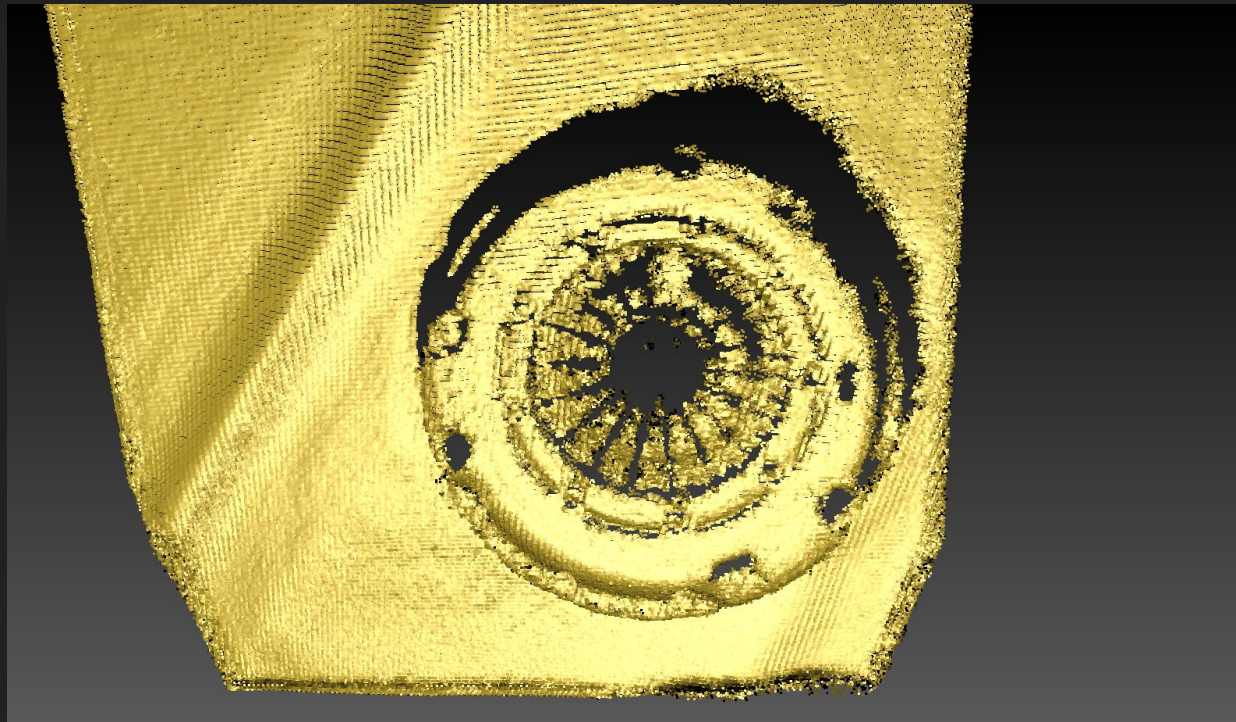
ImageMagic resize



DKN



FDSR



Sources

- <https://www.photoneo.com/products/phoxi-scan-m/>
- <https://www.photoneo.com/3d-model-creation/>
- <https://www.bricsys.com/blog/point-clouds-whats-the-point>
- <https://github.com/jun0kim/DKN>
- <https://www.meshlab.net/>
- <https://arxiv.org/pdf/2104.06174v1.pdf>