Project 9d：Monocular Depth Estimation via Transfer Learning

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Who are we?
Students from Robotics at TU Delft and Autonomous Systems at DTU

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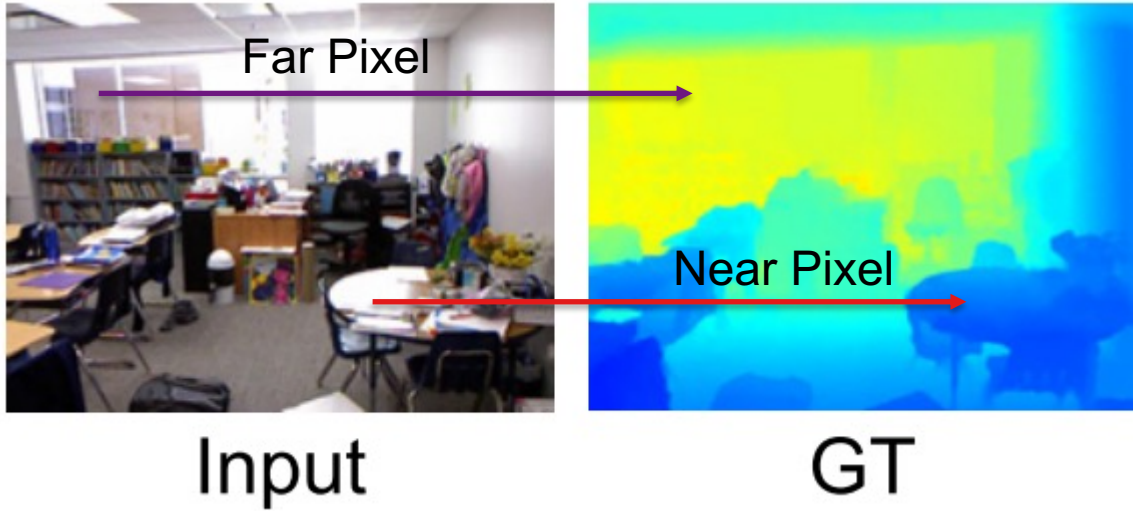
Presentation by Liangchen Sui

Task Description:

- Pixel to pixel regression[1]



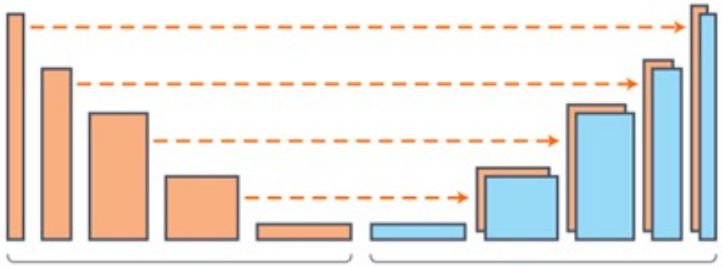
[1]Alhashim, Ibraheem, and Peter Wonka. "High quality monocular depth estimation via transfer learning." *arXiv preprint arXiv:1812.11941* (2018).

Encoder & Decoder Design:

- Encoder
  - Backbone of DenseNet-169 transferred from ImageNet classification

- Decoder
  - Successive bilinear upsampling blocks followed by shallow convolutional layers to realize pixel-pixel regression(high complexity proved to backfire)
  - 1x1 Convs to establish inter-channel connections
  - Skip connections to retrieve information and add high-resolution details

Encoder & Decoder Design:



LAYER	OUTPUT	FUNCTION
INPUT	480 × 640 × 3	
CONV1	240 × 320 × 64	DenseNet CONV1
POOL1	120 × 160 × 64	DenseNet POOL1
POOL2	60 × 80 × 128	DenseNet POOL2
POOL3	30 × 40 × 256	DenseNet POOL3
...	...	...
CONV2	15 × 20 × 1664	Convolution 1 × 1 of DenseNet BLOCK4

UP1	30 × 40 × 1664	Upsample 2 × 2
CONCAT1	30 × 40 × 1920	Concatenate POOL3
UP1-CONVA	30 × 40 × 832	Convolution 3 × 3
UP1-CONVB	30 × 40 × 832	Convolution 3 × 3
UP2	60 × 80 × 832	Upsample 2 × 2
CONCAT2	60 × 80 × 960	Concatenate POOL2
UP2-CONVA	60 × 80 × 416	Convolution 3 × 3
UP2-CONVB	60 × 80 × 416	Convolution 3 × 3
UP3	120 × 160 × 416	Upsample 2 × 2
CONCAT3	120 × 160 × 480	Concatenate POOL1
UP3-CONVA	120 × 160 × 208	Convolution 3 × 3
UP3-CONVB	120 × 160 × 208	Convolution 3 × 3
UP4	240 × 320 × 208	Upsample 2 × 2
CONCAT3	240 × 320 × 272	Concatenate CONV1
UP2-CONVA	240 × 320 × 104	Convolution 3 × 3
UP2-CONVB	240 × 320 × 104	Convolution 3 × 3
CONV3	240 × 320 × 1	Convolution 3 × 3

Encoder

Decoder

Loss Function Design

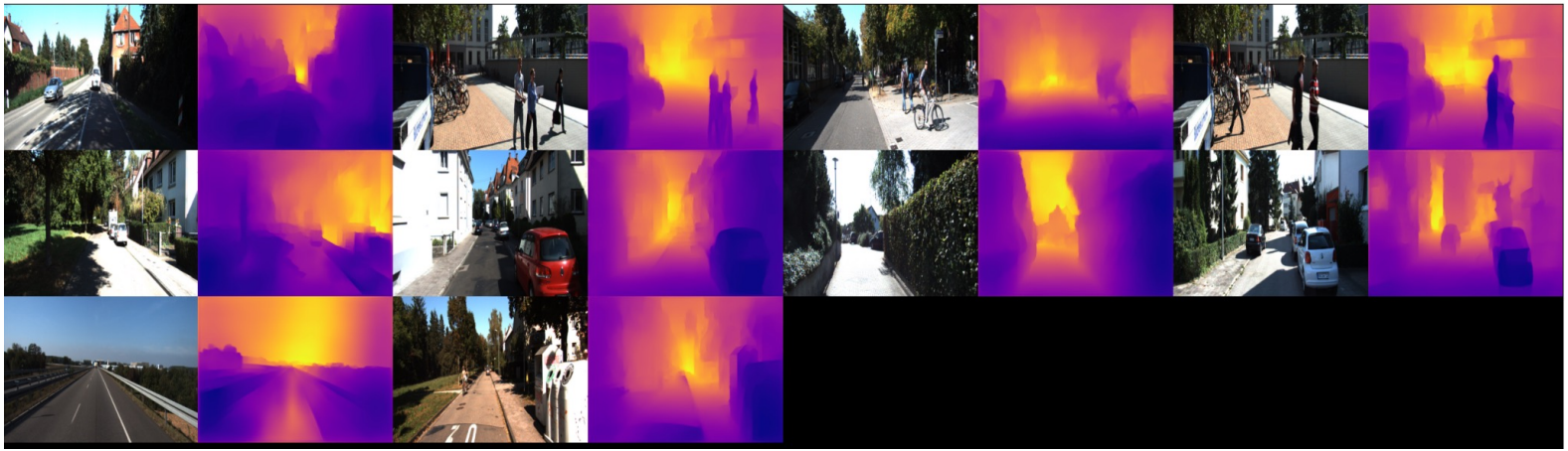
- L1 Loss(Depth + Gradient) + SSIM ➔ High Granularity
- L2 Loss(Depth + Gradient) + SSIM ➔ Fast Convergence
- Berhu Loss(Depth + Gradient) + SSIM ➔ Make a Compromise

Data Augmentation

- To achieve higher generalizations, series of operations simulating natural deformations are implemented on the dataset
  - Random crops
  - Horizontal flips
  - Vertical flips
  - Rotations
  - Affine transformations

Results

- RGB Inputs & Depth Predictions(fine-tunned on KITTI)



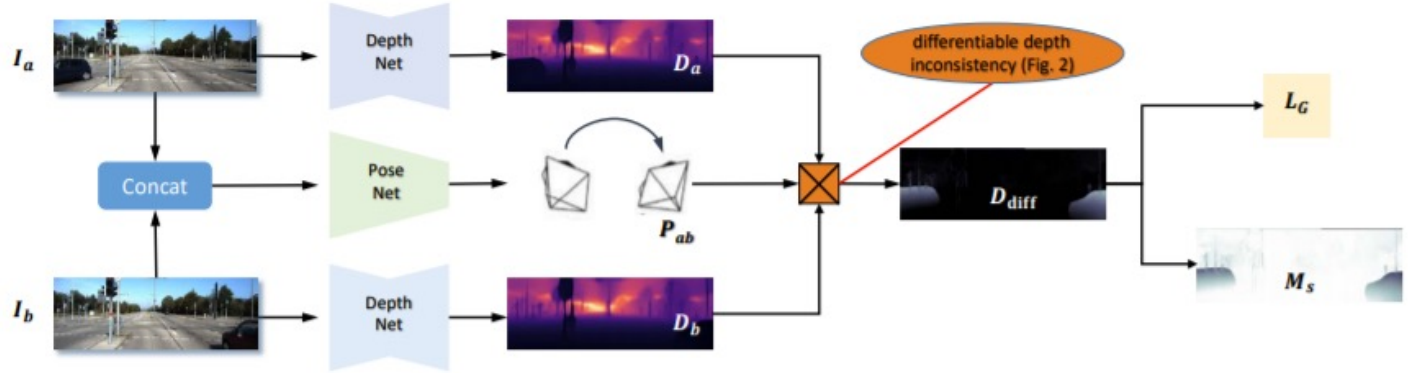
- Evaluation metrics are regretfully not available due to the key files missing in the benchmark

Future Work

- An interesting discovery: specific scenarios such as **outdoors** and **over exposures** are not considerately collected in NYU Depth v2 dataset, which could jeopardize the **robustness** and **generalization** of the model under some extreme circumstances, especially when the **depth values are large and light intensities are high.**

Future Work

- The structure of ideal model based on supervised learning[1] could be used as Depth Net component in unsupervised scale-consistent depth learning from video, which tends to serve as an important part in visual SLAM to provide depth information.



[1]Bian, Jia-Wang, et al. "Unsupervised Scale-consistent Depth Learning from Video." *International Journal of Computer Vision* (2021): 1-17.

Thank you for listening!