Monocular Depth Estimation Based on Convolutional Neural Networks

Group: We Want a GPU
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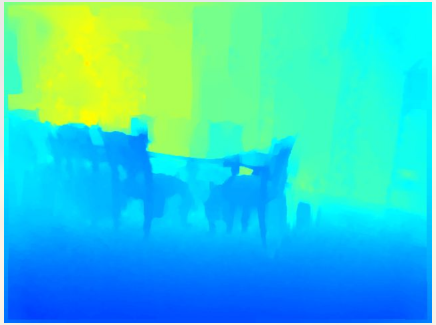
Problem Statement

Problem: Monocular depth estimation

- Predict depth of pixels in a single 2D RGB image

Applications:

- Navigation in robotics, 3D scene reconstruction, augmented reality, etc.



Related Work

DenseDepth[1]

- Used transfer learning on an encoder-decoder framework
- Initialized the encoder with pre-trained denseNet-169

FastDepth[2]

- Applied lightweight model architecture and prune the network
- Achieves similar accuracy, but faster: good for real-time inference

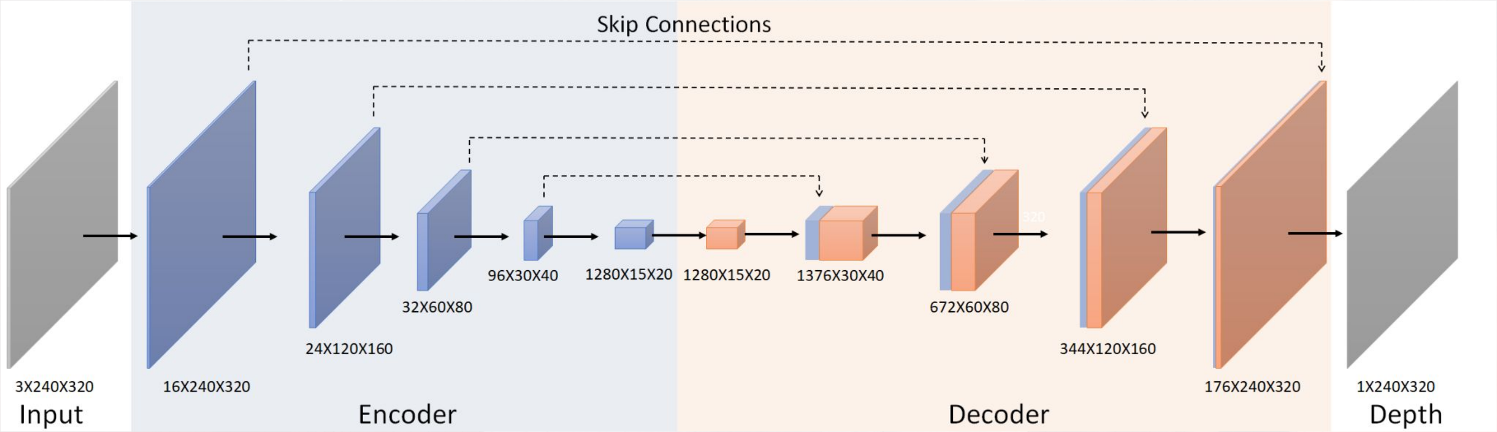
Deep Ordinal Regression[3]

- Applied an SID strategy to discretize depth and utilized ordinal regression
- Avoided complicating network training and reducing resolution of images

Overview

- U-net structure
- Loss function
- Evaluation metrics
- Visualization of results

Model Architecture



- Encoder with transfer learning: mobile net v2/squeeze net
- Decoder with skip connections

Loss Function

$$L(y,\hat{y}) = \lambda L_{depth}(y,\hat{y}) + L_{grad}(y,\hat{y}) + L_{SSIM}(y,\hat{y})$$

$$L_{\text{depth}}(y,\hat{y}) = \frac{1}{n}\sum_{p}^{n} |y_p - \hat{y}_p| .$$

$$L_{grad}(y,\hat{y}) = \frac{1}{n}\sum_{p}^{n} |\boldsymbol{g}_{\mathbf{x}}(y_p,\hat{y}_p)| + |\boldsymbol{g}_{\mathbf{y}}(y_p,\hat{y}_p)| .$$

$$L_{SSIM}(y,\hat{y}) = \frac{1 - SSIM(y,\hat{y})}{2}$$

Experiments & Metrics

1. Encoder-Decoder Structure
   - Mobile net v2
   - Squeeze net

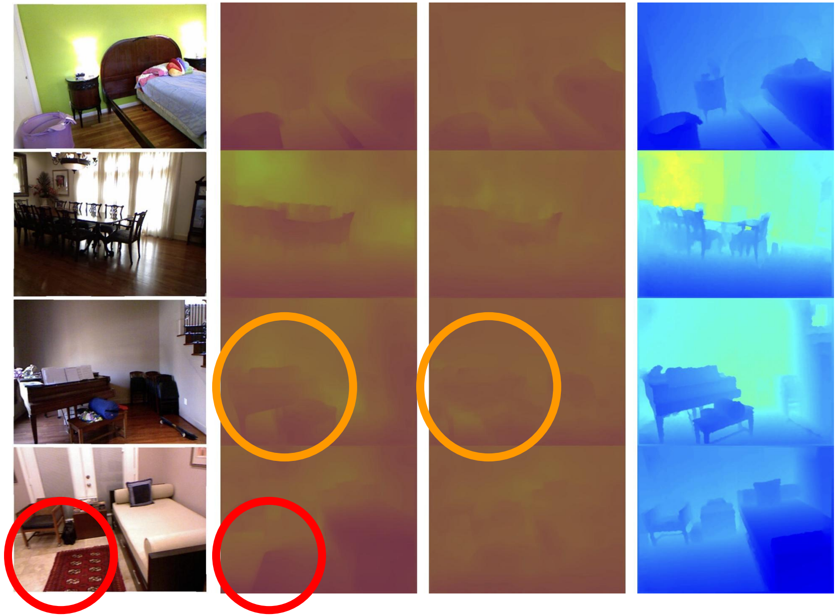
2. Data processing
   - Normalization or not
   - Randomly Gray scaling

1. Average relative error(rel): $\frac{1}{n}\sum_{p}^{n}\frac{|y_p - \hat{y_p}|}{y}$
2. Root mean squared error(rms): $\sqrt{\frac{1}{n}\sum_{p}^{n}(\frac{y_p - \hat{y_p}}{y_p})^2}$
3. Average log10 error: $\frac{1}{n}\sum|\log_{10}(y_p) - \log_{10}(\hat{y_p})|$
4. Threshold accuracy: % of pixels s.t: $\max(\frac{y_p}{\hat{y_p}}, \frac{\hat{y_p}}{y_p}) = \delta < thr$ for $thr = 1.25, 1.25^2, 1.25^3$

Results

	Rel	RMS	$\log_{10}$
Mobile net v2	0.228	0.337	0.088
Squeeze net	0.412	0.575	0.151
	δ_1	δ_2	δ_3
Mobile net v2	0.661	0.891	0.968
Squeeze net	0.405	0.690	0.867

Table 1. Mobile net v2 versus Squeeze net



Input images, Mobile net v2, Squeeze, Ground truth

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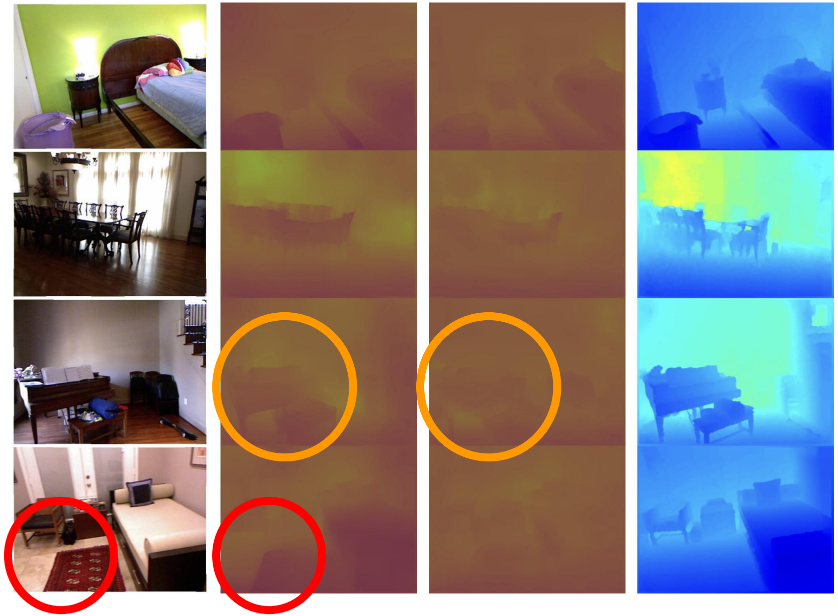
Table 1. Mobile net v2 versus Squeeze net

	Rel	RMS	log_{10}	δ_1
Normalization	0.3175	0.4234	0.1380	0.4176
Grayscale	0.3195	0.4204	0.1379	0.3936
None	0.3501	0.4732	0.1474	0.3974
	δ_2	δ_3	Loss	
Normalization	0.7306	0.9214	45.3805	
Grayscale	0.7364	0.9258	45.5978	
None	0.6989	0.8924	47.1242	

Table 2. Effect of Normalization and Grayscaling



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Thank you!