Monocular Depth Estimation Using Neural Regression Forest

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Monocular Depth Estimation



Input Image



Our prediction

Monocular Depth Estimation



Input Image



Our prediction

• Prior Work:

- Graphical models [Saxena et. al., IJCV 07; Saxena et. al., PAMI 2009; Liu et. al., ICCV 10; Liu et. al., CVPR 2014; Batra et. al., CVPR 12; Lam et. al., CVPR 15]

- Deep learning framework [Eigen et. al., NIPS 14; Liu et. al., CVPR 14; Liu et. al., CVPR 15]

Monocular Depth Estimation



Input Image



Our prediction

• Major challenge:

Limited data for some depths

 Depth range: Make 3D [0 - 80] meters
 NYU v2 [0 - 10] meters



Our Approach: Neural Regression Forest

• Each split node represents a CNN



Neural Regression Forest



- Advantages:
 - Simpler binary decisions
 - Shallow CNNs
 - Parallel loss updates



Augmenting Training Data

- Similar neighboring pixels

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 Similar depths
- Similarity in the image estimated efficiently by bi-lateral filtering

Prediction for *i* th pixel



Evaluation of Robustness



Graceful increase in error for a reduction in the amount of training data

Results on the Benchmark Datasets

	Make3D		NYU v2		
	rel	rms	rel	rms	
Saxena et. al. 2009	0.370	-	0.349	1.214	-
Batra et. al. 2012	0.362	15.8	-	-	Relative (rel): $\frac{1}{N}\sum(d^*-\hat{d} /d^*)$
Liu et. al. 2014	0.338	12.60	0.335	1.06	
Karsch et. al. 2014	0.361	15.10	0.35	1.2	-
Lam et. al. 2015	0.364	-	-	-	- Deetmeen
Liu et. al. 2010	0.379	-	-	-	Root mean $\frac{1}{N}\sqrt{\sum(d^*-\hat{d})^2}$
Eigen et. al. 2014	-	-	0.215	0.907	square (rms): N V 2 V
Liu et. al. 2014	0.307	12.89	0.230	0.824	-
Zhuo et. al. 2015	-	-	0.305	1.04	-
Ours	0.26	12.40	0.187	0.744	-
Error reduction	- 0.04	-0.2	- 0.2	- 0.08	-

Results on the Make3D outdoor Images



Results on the NYUv2 Indoor Images

