InDepth: Real-time Depth Inpainting for Mobile Augmented Reality

Yunfan Zhang (Duke University), **Tim Scargill (Duke University)**, Ashutosh Vaishnav (Aalto University), Gopika Premsankar (University of Helsinki), Mario Di Francesco (Aalto University), Maria Gorlatova (Duke University)









Presentation Contents

- Background and Motivation
- Depth Sensing for Mobile AR
- DNN Design
- Evaluation
 - DNN
 - System
 - User Experience
- Conclusion and Future Work



Mobile Augmented Reality

- Augmented reality (AR): the overlaying of virtual content onto a view of the real world
- Mobile AR facilitates this through portable, handheld or wearable devices
- Wide variety of use cases, from e-commerce to education and medicine





Mobile AR Devices

- Specialized headsets (Microsoft HoloLens 2, Magic Leap One)
- Smartphones and tablets, supported by ARCore (Android) and ARKit (iOS)
- Onboard sensors map environment and track device pose within it







AR Device Depth Sensors

- Headsets and high-end smartphones and tablets equipped with depth sensors
- Time-of-Flight (ToF) cameras provide real-time depth data; low power, high frame rate
- Raw depth maps incomplete due to range limitations and reflectance properties

RGB image

Raw

map

depth





Virtual Object Scale Errors

- Existing depth map completion methods (e.g., [1, 2]) result in inaccurate depth maps, causing errors in the size of rendered virtual objects
- Majority of respondents to our online survey on previous AR experiences indicated virtual object size errors are a somewhat frequent or a very frequent issue in mobile AR



[1] Jonathan T Barron and Ben Poole. 2016. The fast bilateral solver. In ECCV.[2] Yinda Zhang and Thomas Funkhouser. 2018. Deep Depth Completion of a Single RGB-D Image. In IEEE CVPR.

InDepth Paper Contributions

- ToF18K dataset: 18.6K depth maps + RGB
- New DNN architecture which obtains accurate depth maps with latency as low as 8.7ms
- Mean absolute error of depth estimates of 20cm compared to 78cm in ARCore DepthLab

 In a user study 87% more participants rated virtual objects the correct size with InDepth than DepthLab



Time-of-Flight (ToF) Depth Cameras

- Consist of infrared emitter and receiver, measure properties of reflected light to estimate distance
- We focus on indirect ToF: modulate light to detect phase shifts

• Currently used on Samsung Galaxy Note 10+, Huawei P40 Pro, Microsoft HoloLens 2 and Magic Leap One



ToF18K Dataset: Limitations of ToF Cameras

- 18.6K depth maps (plus RGB images) collected on a Samsung Galaxy Note 10+, in variety of indoor scenes
 - 47.2% of total depth pixels were missing
 - 50% of captured maps had more than 40% missing pixels
 - Errors due to distance and surface brightness or orientation



Sample Issues in Depth Maps

- Measurement errors and artifacts caused by:
 - Distant surfaces, surfaces parallel to camera axis
 - Very bright or dark materials
 - Undesired reflections

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10/19

DNN Architecture

- Two-branch encoder to extract features from RGB and depth inputs
- Dilated decoder block for depth data (right)





Data Augmentation and Training

- Trained on Matterport 3D RGB-D dataset [3]
- Depth artifacts added based on our ToF18K dataset
- Custom hybrid loss function: weighted sum of Virtual Normal Loss [4], gradients of depth estimation error, and BerHu loss

[3] Angel Chang, Angela Dai, Thomas Funkhouser, Maciej Halber, Matthias Niessner, Manolis Savva, Shuran Song, Andy Zeng, and Yinda Zhang. 2017. Matterport3D: Learning from RGB-D Data in Indoor Environments. In *International Conference on 3D Vision (3DV)*.
[4] W. Yin, Y. Liu, C. Shen, and Y. Yan. 2019. Enforcing Geometric Constraints of Virtual Normal for Depth Prediction. In *IEEE ICCV*.

Data-Driven DNN Evaluation

Method	MAE (m)	RMSE (m)	1.25	Latency (ms)
Bilateral filtering	0.774	1.978	0.613	1457.1
Markov random fields	0.618	1.675	0.651	685.0
Anisotropic diffusion	0.610	1.653	0.663	896.0
[Zhang and Funkhouser, CVPR 2018]	0.461	1.316	0.781	4036.6
[Huang et al., ICCVW 2019]	0.342	1.092	0.850	70.2
InDepth DNN	0.294	1.008	0.876	8.7

Metrics: MAE: Mean Absolute Error; RMSE: Root Mean Square Error; 1.25: percentage of pixels within the 1.25 error range; inference latency.



Software Components and Testbeds

- Realized with OpenCV, PyTorch, and TensorRT
- Two edge testbeds (workstation-class and embedded-class)





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System Performance Evaluation

Edge testbed	w-class	e-class	Accuracy	MAE (m)	RMSE (m)	1.25
End-to-end	26.3	36.5	Real-world experiments	0.238	0.468	0.941
			Matterport	0.294	1.008	0.876
Communication overhead	13.1	9.2	3D reference			
Image pre- processing	4.5	10.8				
DNN inference	8.7	16.5				



Comparison with State of the Art

• ARCore DepthLab: open-source software to view and interact with depth maps, generated by the ARCore Depth API for Android

Higher depth estimation error than InDepth







User Experience: InDepth vs State of the Art

- Participants rated images of real painting in virtual frame
- 87% more participants rated virtual objects rendered with InDepth of the correct size compared to DepthLab



Conclusions and Future Work

 InDepth DNN infers depth for missing regions in a depth map with a low latency; outperforms state of the art in both data-driven and user evaluations

- Future work includes incorporating technique into a full AR system with 6DoF tracking
- Fascinating opportunities for user studies which explore other types of virtual content errors



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