Fast and Accurate Single-Image Depth Estimation on Mobile Devices, Mobile AI 2021 Challenge: Report

Andrey Ignatov Grigory Malivenko David Plowman Samarth Shukla Radu Timofte
Ziyu Zhang Yicheng Wang Zilong Huang Guozhong Luo Gang Yu Bin Fu
Yiran Wang Xingyi Li Min Shi Ke Xian Zhi guo Cao Jin-Hua Du
Pei-Lin Wu Chao Ge Jiaoyang Yao Fangwen Tu Bo Li Jung Eun Yoo
Kwanggyoon Seo Jialei Xu Zhenyu Li Xianming Liu Junjun Jiang
Wei-Chi Chen Shayan Joya Huanhuan Fan Zhaobing Kang Ang Li
Tianpeng Feng Yang Liu Chuannan Sheng Jian Yin Fausto T. Benavides

Abstract

Depth estimation is an important computer vision problem with many practical applications to mobile devices. While many solutions have been proposed for this task, they are usually very computationally expensive and thus are not applicable for on-device inference. To address this problem, we introduce the first Mobile AI challenge, where the target is to develop an end-to-end deep learning-based depth estimation solutions that can demonstrate a nearly real-time performance on smartphones and IoT platforms. For this, the participants were provided with a new large-scale dataset containing RGB-depth image pairs obtained with a dedicated stereo ZED camera producing high-resolution depth maps for objects located at up to 50 meters. The runtime of all models was evaluated on the popular Raspberry Pi 4 platform with a mobile ARM-based Broadcom chipset. The proposed solutions can generate VGA resolution depth maps at up to 10 FPS on the Raspberry Pi 4 while achieving high fidelity results, and are compatible with any Android or Linux-based mobile devices. A detailed description of all models developed in the challenge is provided in this paper.

1. Introduction

A wide spread of various depth-guided problems related to augmented reality, gesture recognition, object segmentation, autonomous driving and bokeh effect rendering tasks has created a strong demand for fast and efficient single-image depth estimation approaches that can run on portable low-power hardware. While many accurate deep learning-based solutions have been proposed for this problem in the past [46, 16, 14, 47, 48, 42, 15, 10], they were optimized for high fidelity results only while not taking into account computational efficiency and mobile-related constraints, which is essential for tasks related to image processing [23, 24, 37] on mobile devices. This results in solutions requiring powerful high-end GPUs and consuming gigabytes of RAM when processing even low-resolution input data, thus being incompatible with resource-constrained mobile hardware. In this challenge, we change the current depth estimation benchmarking paradigm by using a new depth estimation dataset collected in the wild and by imposing additional efficiency-related constraints on the designed solutions.

When it comes to the deployment of AI-based solutions on portable devices, one needs to take care of the particularities of mobile CPUs, NPs and GPUs to design an efficient model. An extensive overview of mobile AI acceleration hardware and its performance is provided in [33, 30]. According to the results reported in these papers, the latest mobile NPs are already approaching the results of mid-range desktop GPUs released not long ago. However, there are still two major issues that prevent a straightforward deployment of neural networks on mobile devices: a restricted amount of RAM, and a limited and not always efficient support for many common deep learning layers and operators. These two problems make it impossible to process high resolution data with standard NN models, thus requiring a careful adaptation of each architecture to the restrictions of mobile AI hardware. Such optimizations can include network pruning and compression [11, 26, 45, 49, 53], 16-bit / 8-bit [11, 40, 39, 73] and low-bit [9, 65, 38, 50] quantization, device- or NPU-specific adaptations, platform-aware neural architecture search [20, 60, 70, 66], etc.

While many challenges and works targeted at efficient deep learning models have been proposed recently, the evaluation of the obtained solutions is generally performed on
desktop CPUs and GPUs, making the developed solutions not practical due to the above mentioned issues. To address this problem, we introduce the first Mobile AI Workshop and Challenges, where all deep learning solutions are developed for and evaluated on real low-power devices. In this competition, the participating teams were provided with a novel depth estimation dataset containing over 8 thousand RGB-depth image pairs collected in the wild with a stereo ZED 3D camera. Within the challenge, the participants were evaluating the runtime and tuning their models on the Raspberry Pi 4 ARM based single-board computer used as a target platform for many embedded machine learning projects. The final score of each submitted solution was based on the runtime and fidelity results, thus balancing between the image reconstruction quality and efficiency of the proposed model. Finally, all developed solutions are fully compatible with the TensorFlow Lite framework, thus can be deployed and accelerated on any mobile platform providing AI acceleration through the Android Neural Networks API (NNAPI) or custom TFLite delegates.

This challenge is a part of the MAI 2021 Workshop and Challenges consisting of the following competitions:

- Learned Smartphone ISP on Mobile NPUs [22]
- Real Image Denoising on Mobile GPUs [21]
- Quantized Image Super-Resolution on Edge SoC NPUs [31]
- Real-Time Video Super-Resolution on Mobile GPUs [28]
- Single-Image Depth Estimation on Mobile Devices
- Quantized Camera Scene Detection on Smartphones [25]
- High Dynamic Range Image Processing on Mobile NPUs

The results obtained in the other competitions and the description of the proposed solutions can be found in the corresponding challenge papers.

2. Challenge

To develop an efficient and practical solution for mobile-related tasks, one needs the following major components:

1. A high-quality and large-scale dataset that can be used to train and evaluate the solution;
2. An efficient way to check the runtime and debug the model locally without any constraints;
3. An ability to regularly test the runtime of the designed neural network on the target mobile platform or device.

This challenge addresses all the above issues. Real training data, tools, and runtime evaluation options provided to the challenge participants are described in the next sections.

2.1. Dataset

To get real and diverse data for the considered challenge, a novel dataset consisting of RGB-depth image pairs was collected using the ZED stereo camera capable of shooting 2K images. It demonstrates an average depth estimation error of less than 0.2m for objects located closer than 8 meters [55], while more coarse predictions are also available for distances of up to 50 meters. Around 8.3K image pairs were collected in the wild over several weeks in a variety of places. For this challenge, the obtained images were down-scaled to VGA resolution (640 × 480 pixels) that is typically used on mobile devices for different depth-related tasks. The original RGB images were then considered as inputs, and the corresponding 16-bit depth maps — as targets. A sample RGB-depth image pair from the collected dataset is demonstrated in Fig. 1.

1https://www.stereolabs.com/zed/
2.2. Local Runtime Evaluation

When developing AI solutions for mobile devices, it is vital to be able to test the designed models and debug all emerging issues locally on available devices. For this, the participants were provided with the AI Benchmark application [30, 33] that allows to load any custom TensorFlow Lite model and run it on any Android device with all supported acceleration options. This tool contains the latest versions of Android NNAPI, TFLite GPU, Hexagon NN, Samsung Eden and MediaTek Neuron delegates, therefore supporting all current mobile platforms and providing the users with the ability to execute neural networks on smartphone NPUs, APUs, DSPs, GPUs and CPUs.

To load and run a custom TensorFlow Lite model, one needs to follow the next steps:

1. Download AI Benchmark from the official website or from the Google Play and run its standard tests.
2. After the end of the tests, enter the PRO Mode and select the Custom Model tab there.
3. Rename the exported TFLite model to `model.tflite` and put it into the Download folder of the device.
4. Select mode type (INT8, FP16, or FP32), the desired acceleration/inference options and run the model.

These steps are also illustrated in Fig. 2.

2.3. Runtime Evaluation on the Target Platform

In this challenge, we use the Raspberry Pi 4 single-board computer as our target runtime evaluation platform. It is based on the Broadcom BCM2711 chipset containing four Cortex-A72 ARM cores clocked at 1.5 GHz and demonstrates AI Benchmark scores comparable to entry-level Android smartphone SoCs [6]. The Raspberry Pi 4 supports the majority of Linux distributions, Windows 10 IoT build as well as Android operating system. In this competition, the runtime of all solutions was tested using the official TensorFlow Lite 2.5.0 Linux build [63] containing many important performance optimizations for the above chipset, the default Raspberry Pi OS was installed on the device.

Within the challenge, the participants were able to upload their TFLite models to the runtime validation server connected to a real Raspberry Pi 4 board and get instantaneous feedback: the runtime of their solution or an error log if the model contains some incompatible operations. The same setup was also used for the final runtime evaluation.

2.4. Challenge Phases

The challenge consisted of the following phases:

I. Development: the participants get access to the data and AI Benchmark app, and are able to train the models and evaluate their runtime locally;

II. Validation: the participants can upload their models to the remote server to check the fidelity scores on the validation dataset, to get the runtime on the target plat-
form, and to compare their results on the validation leaderboards;

III. Testing: the participants submit their final results, codes, TensorFlow Lite models, and factsheets.

2.5. Scoring System

All solutions were evaluated using the following metrics:

• Root Mean Squared Error (RMSE) measuring the absolute depth estimation accuracy,

• Scale Invariant Root Mean Squared Error (si-RMSE) measuring the quality of relative depth estimation (relative position of the objects),

• Average log\textsubscript{10} and Relative (REL) errors [48],

• The runtime on the target Raspberry Pi 4 device.

The score of each final submission was evaluated based on the next formula (\( C \) is a constant normalization factor):

\[
\text{Final Score} = \frac{2^{0.20 \cdot \text{si-RMSE}}}{C \cdot \text{runtime}}.
\]

During the final challenge phase, the participants did not have access to the test dataset. Instead, they had to submit their final TensorFlow Lite models that were subsequently used by the challenge organizers to check both the runtime and the fidelity results of each submission under identical conditions. This approach solved all the issues related to model overfitting, reproducibility of the results, and consistency of the obtained runtime/accuracy values.

3. Challenge Results

From above 140 registered participants, 10 teams entered the final phase and submitted valid results, TensorFlow models, codes, executables and factsheets. Table 1 summarizes the final challenge results and reports si-RMSE, RMSE, LOG10 and REL measures and runtime numbers for each submitted solution on the final test dataset and on the target evaluation platform. The proposed methods are described in section 4, and the team members and affiliations are listed in Appendix A.

3.1. Results and Discussion

All proposed solutions are relying on the encoder-decoder based architecture as it allows both to perform heavy image manipulations and to reduce the computational complexity of the model by doing the majority of processing at lower scales / resolutions. Nearly all models used standard image classification models in their encoder module extracting features from the input images. Teams Tencent GY-Lab, SMART, Airia-Team1 and CFL2 adopted MobileNets for this as they are already optimized for low-power devices and can achieve a very good runtime on the majority of mobile platforms. The best fidelity results were, however, obtained by team HIT-AIIA that used the EfficientNet-B1 network for feature generation. To improve the models’ accuracy, skip connections between the encoder and decoder blocks were added in almost all architectures. Another popular approach resulting in better depth prediction was to use knowledge distillation: a larger model was first trained for the same task, and then its outputs or intermediate features were used as additional targets for the final small network. In particular, this approach was used by the challenge winner, team Tencent GY-Lab, that outperformed all other methods by a huge margin, being able to get both good fidelity scores and to achieve more than 10 FPS on the target Raspberry Pi 4 device. Notably, this solution is a magnitude faster than the FastDepth [69] model known as one of the most efficient ones for this task.

To further benchmark the efficiency of the designed solutions, we additionally tested their performance on several popular smartphone chipsets. The runtime results demonstrated in Table 2 were measured with the AI Benchmark using the TFLite GPU delegate [43] compatible with all mobile devices supporting OpenCL or OpenGL 3.0+. In almost all cases, the runtime of the proposed networks is less than half a second except for the solution from 3dv oppo: due to the issues caused by PyTorch to TFLite conversion, it contains several ops supported neither by TFLite delegates nor by Android NNAPI, thus this model was executed on CPU, same as networks from Airia-Team1 and CFL2. The solution from team Tencent GY-Lab demonstrated more than 75 FPS on all considered SoCs, thus be-
Table 2. The speed of the proposed solutions on several popular mobile GPUs. The runtime was measured with the AI Benchmark app using the TFLite GPU delegate [43]. * Solutions from teams Airia-Team1, CFL2 and 3dv oppo are not compatible with neither TFLite delegates nor Android NNAPI due to the issues related to PyTorch → TFLite conversion, thus were executed on mobile CPUs.

| Mobile SoC | Snapdragon 888 | Snapdragon 855 | Dimensity 1000 | Dimensity 800 | Exynos 2100 | Exynos 990 | Kirin 990 5G | Kirin 990 |
|------------|----------------|----------------|---------------|---------------|-------------|-------------|--------------|---------|
| GPU        | Adreno 660, ms | Adreno 640, ms | Mali-G77 MP9, ms | Mali-G57 MP4, ms | Mali-G78 MP14, ms | Mali-G77 MP11, ms | Mali-G76 MP16, ms | Mali-G76 MP10, ms |
| Tencent GY-Lab | 3.5   | 5.7  | 8.6  | 11  | 5.7  | 12  | 8.8  | 9.3   |
| SMART      | 33    | 60   | 65   | 106 | 37   | 53  | 48   | 58    |
| Airia-Team1 * | 283   | 321  | 295  | 447 | 248  | 270 | 337  | 351   |
| YTL        | 35    | 70   | 71   | 104 | 36   | 52  | 54   | 65    |
| CFL2 *     | 121   | 179  | 166  | 277 | 117  | 170 | 179  | 188   |
| HIT-AIIA   | 95    | 175  | 149  | 320 | 101  | 137 | 142  | 183   |
| weichi     | 7.1   | 11   | 23   | 43  | 13   | 18  | 18   | 22    |
| MonoVision Palace | 77  | 128  | 119  | 247 | 71   | 97  | 101  | 129   |
| 3dv oppo * | 3672  | 4346 | 4053 | 4832 | 4071 | 3649 | 3753 | 4107   |

Figure 3. The model architecture and the structure of the Feature Fusion Module (FFM) proposed by team Tencent GY-Lab.
4.2. SMART

Same as the previous solution, team SMART used a MobileNet-based encoder module for feature extraction and applied knowledge distillation to train the network. The architecture of the proposed solution is demonstrated in Fig. 5: the standard FastDepth [69] architecture with a MobileNet-V1 backbone is used for the main (student) model. The larger teacher network consists of a ResNeSt-101 [72] based encoder and a decoder block [71] with the adaptive output layer on top of it. The representation ability of a pre-trained teacher model is transferred to the student network via knowledge distillation: a pairwise distillation loss is adopted to force the student network to output feature maps that are similar to the outputs of the corresponding layers of the teacher network. The distillation loss is computed in two steps (Fig. 4): let \( F_t \in \mathbb{R}^{h \times w \times c_1} \) and \( F_s \in \mathbb{R}^{h \times w \times c_2} \) be the feature maps with the same spatial resolution from the teacher and the student models, respectively, then the affinity maps are first computed as:

\[
a_{ij} = \frac{f^T_i f_j}{(\|f_i\|_2 \times \|f_j\|_2)},
\]

where \( f \) denotes one row of the feature map \( (F_t \text{ or } F_s) \). Next, the mean square error is computed between the affinity maps obtained for student and teacher models:

\[
\mathcal{L}_{pa}(S, T) = \frac{1}{w \times h} \sum_i \sum_j (a^s_{ij} - a^t_{ij})^2.
\]

Besides that above knowledge distillation loss, two other metrics are used to train the student model. The scale invariant loss [14] is used to measure the discrepancy between the output of the student network and the ground truth depth map:

\[
\mathcal{L}_s(d, d^*) = \frac{1}{n} \sum_i g_i^2 - \frac{1}{n^2} (\sum_i g_i)^2,
\]

where \( d \) and \( d^* \) are the predicted and the ground truth depth maps, and \( g_i = \log d_i - \log d^*_i \) is the corresponding error in log space. Finally, the scale-invariant gradient matching loss [57] is defined as:

\[
\mathcal{L}_{reg}(d, d^*) = \frac{1}{M} \sum_{k=1}^{K} \sum_{i=1}^{M} (|\nabla_x R^k_i| + |\nabla_y R^k_i|),
\]

where \( R_i = d - d^* \), and \( R^k \) denotes the difference between the disparity maps at scale \( k = 1, 2, 3, 4 \) (the resolution of the feature maps is halved at each level). The final loss function is then defined as:

\[
\mathcal{L} = 10 \cdot \mathcal{L}_s(d, d^*) + 0.1 \cdot \mathcal{L}_{reg}(d, d^*) + 1000 \cdot \mathcal{L}_{pa}(S, T).
\]

The model was trained using Adam for 100 epochs with an initial learning rate of \( 1 \times 10^{-3} \) and a polynomial decay with a power of 0.9. A more detailed description of the model, design choices and training procedure is provided in [68].
4.3. Airia-Team1

Figure 6 demonstrates the architecture developed by Airia-Team1. The authors proposed an encoder-decoder model, where MobileNet-V3 [20] network is used for feature extraction, same as in the previous two solutions. The resulting features are fed to three residual feature distillation blocks (RFDB), each one composed of three residual blocks (SRB) and several convolutional and concatenation layers. The refined features obtained after these blocks are then passed to a 5-layer decoder producing the final predictions, several skip connections are additionally used to speed-up the training. The pixel-wise depth loss [7] was used as the target loss function. The model parameters were optimized using Adam with a learning rate of $1e^{-4}$ multiplied by 0.6 each 100 epochs. A batch size of 8 was used during the training, random flips were additionally applied for data augmentation.

4.4. YTL

The authors proposed a U-net based architecture where the ResNet-18 [18] model is used for feature extraction. The input RGB image was resized to 320×240 resolution and then concatenated with an X/Y meshgrid (containing centered pixel coordinates) to form a 5-channel tensor passed to the model. The output of the model was also upsampled from 320×240 to the target 640×480 resolution using one bilinear resize layer on top of it. The network was trained to minimize a combination of the Mean Absolute Error (MAE) and gradient losses using Adam optimizer.

4.5. CFL2

Team CFL2 based its solution on the PyDNet [56, 3] model. The input image was downscaled to 256×256 pixels and then passed to the MobileNetV2 [59] encoder. While the original PyDNet model produces several outputs at multiple scales, the authors used only the highest one that corresponds to the target resolution to reduce the computational complexity of the model. Since the PyDNet is originally producing 128×128px images, they were additionally upsampled to the target resolution using one bilinear resize layer. The scale invariant data loss [14] and the scale-invariant gradient matching loss [57] were used to train the model for 2M iterations using Adam with a learning rate of $1e^{-4}$.

4.6. HIT-AIIA

The model proposed by HIT-AIIA is using the EfficientNet-B1 network [61] as an encoder to extract features from the input images (Fig. 8). The outputs from its last layer are passed to the Non-Local block [67] that effectively improves the accuracy of the model. The authors used a combination of the bilinear upsampling, convolutional and Leaky ReLU layers in the decoder module predicting the final depth map. Additional skip connections were added to
speed-up the training process and improve the fidelity results. The model was trained to minimize RMSE loss function using Adam with a learning rate of $1e^{-4}$ and a batch size of 6. Image mirroring and flipping as well as color alteration were used for data augmentation.

4.7. weichi

Team weichi used the standard U-Net [58] architecture with a reduced by a factor of 8 number of feature maps in each layer. Same as in [52], the authors added batch normalization after each convolution in the encoder block. To improve the accuracy of the model, knowledge distillation [19] was additionally applied during the training process: a larger U-Net model (with an increased number of channels) was first trained on the same dataset using the RMSE loss function. Next, the main student network was minimizing a combination of the RMSE loss between its outputs and the target depth maps, and the MSE loss between its outputs and the outputs of the larger network (Fig. 9). Both models were trained using Adam optimizer with a learning rate of $1e^{-4}$ reduced by a magnitude after the 20th and the 25th epoch.

4.8. MonoVision Palace

Team MVP proposed a Depth Attention UNet (DA-UNet) architecture demonstrated in Fig. 10. The input image was first passed to the EfficientNet-Edge-TPU-S [17] model with removed hard-swish activations and squeeze-and-excitation blocks to reduce the latency. Its outputs were then processed by the decoder block composed of convolution, upsampling, Leaky ReLU and Gated Attention Blocks (GA) [54] where ReLU and sigmoid activations were replaced with Leaky ReLUs and hard-sigmoid ops, respectively. The model was trained using the same metrics as in [4]: the point-wise $L_1$ loss, the gradient $L_1$ loss, and the SSIM loss function. Adam was used to optimize the model parameters for 30 epochs with an initial learning rate of $1e^{-4}$ reduced by a magnitude after the 20th and the 25th epoch.

4.9. 3dv oppo

The authors directly used the BTS model [44] demonstrated in Fig 11. This network is composed of the dense feature extractor (the ResNet model), the contextual information extractor (ASPP), the local planar guidance layers and their dense connection for final depth estimation. The same training setup and the target loss functions as in [44] was used except for the learning rate that was set to $5e^{-5}$.

4.10. MegaUe

Team MegaUe trained a standard U-Net like architecture (Fig. 12) with one additional 2x image downsampling and upsampling layers at the begging and at the top of the model, respectively. The model was first pre-trained on the MegaDepth dataset [46] using the same metrics as in the original paper: the ordinal, data and gradient matching losses. Then, the model was fine-tuned on the challenge data using the last two loss functions.

5. Additional Literature

An overview of the past challenges on mobile-related tasks together with the proposed solutions can be found in the following papers:
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A. Teams and Affiliations

Mobile AI 2021 Team

**Title:**
Mobile AI 2021 Challenge on Single-Image Depth Estimation on Mobile Devices

**Members:**
Andrey Ignatov\(^1,3\) (andrey@vision.ee.ethz.ch), Grigory Malivenko (grigory.malivenko@gmail.com), David Plowman\(^2\) (david.plowman@raspberrypi.com), Samarth Shukla\(^1\) (samarth.shukla@vision.ee.ethz.ch), Radu Timofte\(^1,3\) (radu.timofte@vision.ee.ethz.ch)

**Affiliations:**
\(^1\) Computer Vision Lab, ETH Zurich, Switzerland
\(^2\) Raspberry Pi (Trading) Ltd
\(^3\) AI Witchlabs, Switzerland

**Tencent GY-Lab**

**Title:**
A Simple Baseline for Fast and Accurate Depth Estimation on Mobile Devices [74]

**Members:**
Ziyu Zhang (parkzyzhang@tencent.com), Yicheng Wang, Zilong Huang, Guozhong Luo, Gang Yu, Bin Fu

**Affiliations:**
Tencent GY-Lab, China

**SMART**

**Title:**
Knowledge Distillation for Fast and Accurate Monocular Depth Estimation on Mobile Devices [68]

**Members:**
Yiran Wang (wangyiran@hust.edu.cn), Xingyi Li, Min Shi, Ke Xian, Zhiguo Cao

**Affiliations:**
Key Laboratory of Image Processing and Intelligent Control, Ministry of Education, School of Artificial Intelligence and Automation, Huazhong University of Science and Technology, China

**Airia-Team1**

**Title:**
Monocular Depth Estimation based on MobileNetV3Small

**Members:**
Jin-Hua Du (2982192572@qq.com), Pei-Lin Wu, Chao Ge

**Affiliations:**
Nanjing Artificial Intelligence Chip Research, Institute of Automation, Chinese Academy of Sciences, China

**YTL**

**Title:**
U-Net with Pixel Position Encoding for Monocular Depth Estimation

**Members:**
Jiaoyang Yao (jiaoyangyao@gmail.com), Fangwen Tu, Bo Li

**Affiliations:**
Black Sesame Technologies Inc., Singapore

**CFL2**

**Title:**
Lightfast Depth Estimation

**Members:**
Jung Eun Yoo (jey920@kaist.ac.kr), Kwanggyoon Seo

**Affiliations:**
Visual Media Lab, KAIST, South Korea

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Figure 12. U-Net model proposed by MegaUe team.
HIT-AIIA

Title: EfficientNet Encoder with Non-Local Module for Monocular Depth Estimation
Members: Jialei Xu (20S003044@stu.hit.edu.cn), Zhenyu Li, Xianming Liu, Junjun Jiang
Affiliations: Harbin Institute of Technology, China
Peng Cheng Laboratory, China

weichi

Title: Distillation on UNet
Members: Wei-Chi Chen (ne6094041@gs.ncku.edu.tw)
Affiliations: Multimedia and Computer Vision Laboratory, National Cheng Kung University, Taiwan
http://mmcv.csie.ncku.edu.tw/

MVP - MonoVision Palace

Title: DA-UNet: Depth Attention UNet for Monocular Depth Estimation
Members: Shayan Joya (joya.shayan@gmail.com)
Affiliations: Samsung Research UK, United Kingdom

3dv oppo

Title: Accurate Monocular Depth Estimation Using BTS
Members: Huanhuan Fan (fanhuanhuan@oppo.com), Zhaobing Kang, Ang Li, Tianpeng Feng, Yang Liu, Chuannan Sheng, Jian Yin
Affiliations: OPPO Research Institute, China

MegaUe

Title: Mega-Udepth for Monocular Depth Estimation
Members: Fausto T. Benavides (fausto.tapiabenavides@gmail.com)
Affiliations: ETH Zurich, Switzerland

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