CH_3Depth: Efficient and Flexible Depth Foundation Model with Flow Matching

Supplementary Material

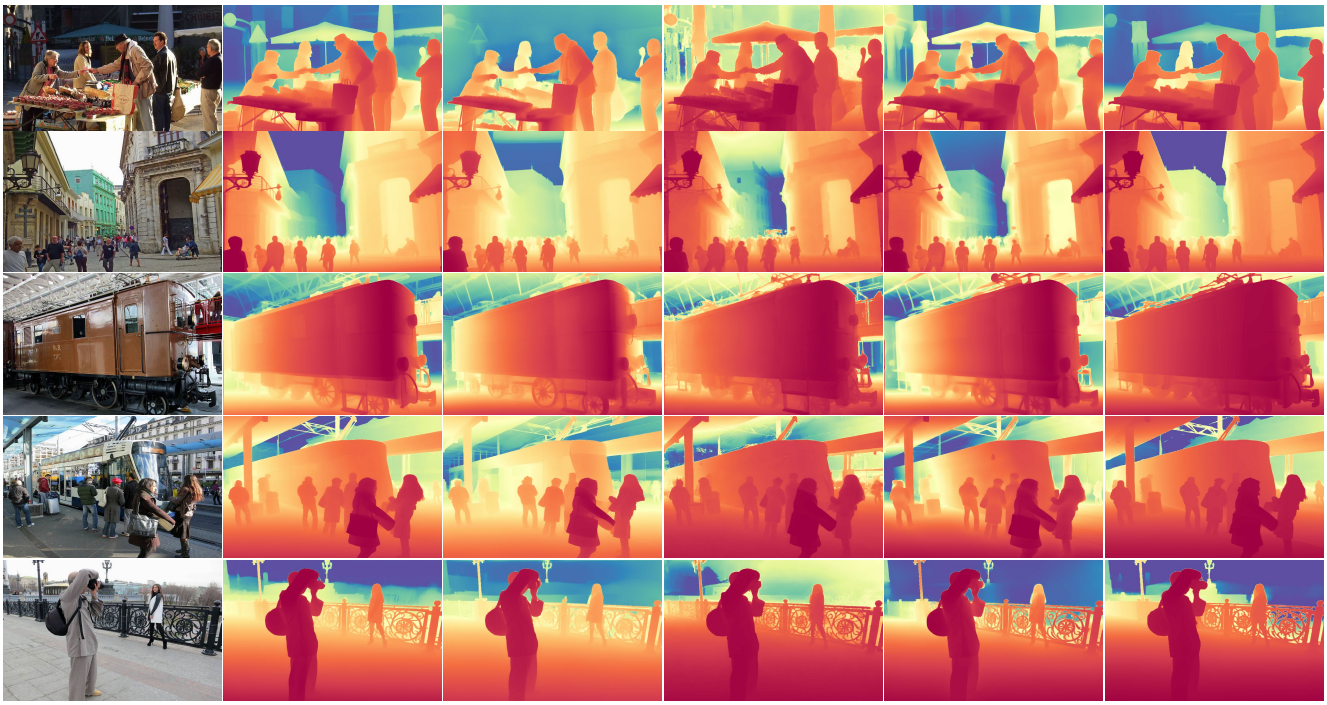

Figure 5. **More Qualitative Comparisons.** We present more qualitative comparisons with other methods on web images in the supplementary materials.

I. More Qualitative Comparisons

We present more qualitative comparisons in the supplementary materials. As shown in Fig. 5, CH_3Depth outperforms the current state-of-the-art discriminative and generative methods [17, 19, 25, 57] in both details and spatial structures.

II. Evaluation Metric

We adopt the OPW introduced by FMNet [49] to evaluate the temporal consistency, which can be specifically expressed as:

$$\mathcal{L}_t(n, n-1) = \frac{1}{M}\sum_{j=1}^{M} O^{(j)}_{n\Rightarrow n-1} \|\hat{D}^{(j)}_n - \bar{D}^{(j)}_{n-1}\|_1 \,, \qquad OPW = \frac{1}{N-1}\sum_{n=2}^{N} \mathcal{L}_t(n, n-1)\,. \tag{10}$$

where $\bar{D}_{n-1}$ represents the predicted depth $\hat{D}_{n-1}$ warped by the optical flow $FL_{n\Rightarrow n-1}$. We adopt the GMFlow [54] for optical flow as prior arts [49, 50]. $O_{n\Rightarrow n-1}$ is the mask calculated as [6, 49] and M denotes pixel numbers.

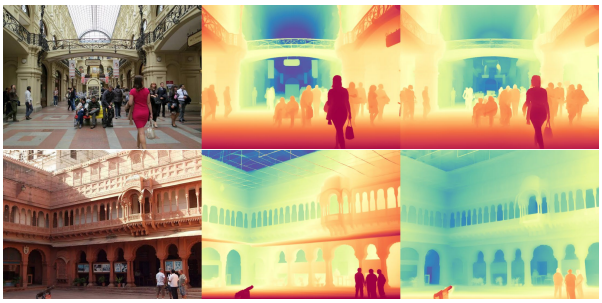

Figure 6. **Corner Cases Presentation.**

III. Failure Cases

Some failure cases of our CH_3Depth are shown in Fig. 6. The potential degradation of edge performance (the thin lines in the sky and the elaborate patterns in the railing) mainly comes from the image quality of RGB itself and the information loss caused by VAE encoding and decoding, which is also the direction of future work.

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