The Temporal Opportunist: Self-Supervised Multi-Frame Monocular Depth

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www.github.com/nianticlabs/manydepth

Abstract

Self-supervised monocular depth estimation networks are trained to predict scene depth using nearby frames as a supervision signal during training. However, for many applications, sequence information in the form of video frames is also available at test time. The vast majority of monocular networks do not make use of this extra signal, thus ignoring valuable information that could be used to improve the predicted depth. Those that do, either use computationally expensive test-time refinement techniques or off-the-shelf recurrent networks, which only indirectly make use of the geometric information that is inherently available.

We propose ManyDepth, an adaptive approach to dense depth estimation that can make use of sequence information at test time, when it is available. Taking inspiration from multi-view stereo, we propose a deep end-to-end cost volume based approach that is trained using self-supervision only. We present a novel consistency loss that encourages the network to ignore the cost volume when it is deemed unreliable, e.g. in the case of moving objects, and an augmentation scheme to cope with static cameras. Our detailed experiments on both KITTI and Cityscapes show that we outperform all published self-supervised baselines, including those that use single or multiple frames at test time.

1. Introduction

Knowing the depth to each pixel in an image has proved to be a useful and versatile tool, with applications ranging from augmented reality [59], autonomous driving [22], through to 3D reconstruction [64]. While specialist hardware can give per-pixel depth, e.g. from structured light or Lidar sensors, a more attractive approach is to only require a single RGB camera. Many recent monocular depth from RGB methods are trained using only self-supervision, which removes the need for expensive hardware to capture training depth data [21, 99, 23, 26]. While these approaches appear to be very promising, their test-time depth estimation performance is not yet on a par with specialist depth hardware or deep multi-view methods [73].

In an attempt to close this performance gap, we observe that in most practical scenarios more than one frame is available at test time e.g. from a camera on a moving vehicle or micro-baseline frames from a phone camera [32, 41]. Yet these additional frames are typically not exploited by current monocular methods. In this work, we use these additional frames at both training and test time, when they are available, to self-supervise a multi-frame depth estimation system. We show that a straightforward application of self-supervised training to a multi-view plane-sweep stereo architecture produces poor results, significantly worse than self-supervised single frame networks. To overcome this, we introduce several innovations to address issues caused by moving objects, scale ambiguity, and static cameras. We call our resultant multi-frame system ManyDepth.

We make the following three contributions:

1. A novel self-supervised multi-frame depth estimation model that combines the strengths of monocular and multi-view depth estimation by making use of multiple frames at test time, when they are available.

2. We show that moving objects and static scenes significantly impact self-supervised multi-view matching approaches, and we introduce efficient losses and train-
ing solutions to alleviate this problem.

3. We propose an adaptive cost volume to overcome the scale ambiguity arising from self-supervised training on monocular sequences. To the best of our knowledge, this is the first time cost volume extents have been learned from data rather than set as parameters.

Our ManyDepth model outperforms existing single and multi-frame approaches on KITTI and Cityscapes.

2. Related work

2.1. Monocular depth estimation

The goal of monocular depth estimation is to predict the depth of each pixel in a single input image. Supervised approaches either make use of dense supervision from depth sensors e.g. [15, 14, 20] or sparse supervision from human annotations e.g. [8]. Self-supervised methods remove the limitation of requiring ground truth depth supervision, instead training with image-reconstruction losses using stereo pairs [87, 21, 23] or monocular video sequences [99].

Recent advances in self-supervised training have focused on addressing various challenges resulting from learning from images alone e.g. more robust image reconstruction losses [26, 72], discrete rather than continuous depth predictions [56, 25, 40], feature space reconstruction losses [93, 72], sparse automatically generated depth supervision [49, 83], occlusion handling [26], improved network architectures [28], and moving objects during training [69, 24, 26, 78, 92, 9, 3, 75, 48, 53] and at test time [54]. Our underlying monocular architecture is based on [24], and could similarly benefit from many of the above enhancements.

2.2. Multi-frame monocular depth estimation

There is a growing number of works that extend existing self-supervised monocular models so that they can leverage temporal information at test time to improve the quality of the predicted depth. It is worth noting that there are also several non-deep-learning methods that also aim to produce consistent sequential depth estimates e.g. [96, 44], in addition to conventional SLAM based methods [65, 63, 16, 89], and SLAM methods that integrate a monocular depth estimation network [74, 4, 52]. However, here we focus on state-of-the-art neural network based depth estimation.

Test-time refinement approaches adapt monocular methods to use sequence information at test time e.g. [5, 9, 59, 62, 72, 51]. As self-supervised training does not require any ground truth depth supervision, the same losses used during training can be applied to the test frames to update the network’s parameters. The downside is that this necessitates the additional computation of multiple forward and backward model passes for a set of test frames, potentially taking several seconds to perform per set [62, 59], although one additional backward pass can be effective and fast [51].

| Needs Depth | Needs Pose | Needs Object Motion | Single Frame | Multi Frame |
|-------------|------------|---------------------|--------------|------------|
| Train       | Test       |                     |              |            |
| Two Frame e.g. [2] | Yes | Yes | No | No | No | Yes |
| Supervised MVS e.g. [37] | Yes | Yes | Yes | No | No | Yes |
| Self-sup MVS e.g. [46] | No | Yes | Yes | No | No | Yes |
| Supervised MD e.g. [20] | Yes | No | No | Yes | Yes | No |
| Self-sup MD e.g. [99] | No | No | No | Yes | Yes | No |

| ManyDepth (Ours) | No | No | No | Yes | Yes | Yes |

Table 1. Comparison of existing approaches that estimate depth from collections of images. Our approach requires no ground-truth supervision and is robust to object motion. MVS stands for Multi-View Stereo, and MD stands for Monocular Depth.

A second broad group of approaches combine traditional monocular networks with recurrent layers to process sequences of frames e.g. [66, 81, 50, 97]. A related approach uses pairs of sequential frames at test time, sharing features between the pose and depth modules [79] or computing depth-from-flow [88]. These approaches are much more efficient compared to test-time refinement, but they can be more computationally demanding during training due to the need to extract features from multiple frames in a sequence. A further limitation of these methods is that they do not explicitly reason about geometry during inference; they simply rely on the network having learned how to extract meaningful temporal representations.

Our experiments show that our approach often outperforms test-time refinement in terms of accuracy while retaining the efficiency of recurrent methods at inference.

2.3. Deep multi-view depth estimation

Our problem of predicting depth from multiple frames is related to multi-view depth estimation. While early deep stereo methods used mostly convolutional layers to map from images pairs to depth using ground-truth supervision e.g. [61, 77, 55], [45] showed that integrating a plane-sweep stereo cost volume significantly improved results. Recent approaches improved the underlying architectures and contributed more effective ways of regularizing the cost volume [7, 94, 95, 10]. It is also possible to train stereo networks without ground truth supervision [98, 82, 1, 36], but these models are typically outperformed by supervised variants. Some works fuse conventional matching-based stereo estimation with monocular depth cues [71, 60, 17]. In contrast, we do not require stereo pairs during training or testing.

A more general version of the stereo-matching problem is multi-view stereo (MVS), which operates on unordered image collections. Early deep MVS methods used memory-expensive 3D grid representations e.g. [39, 43]. Current supervised approaches, e.g. [37, 80, 91, 38, 57], utilize cost volumes but assume ground truth depth and camera poses
are available for training. They often require camera poses at test time too; which can be refined from an initial estimate [84, 56]. Some methods can predict pose at test time, but they still need to be trained with supervision e.g. [77].

Similar to our approach, [56, 35] process sequences of frames at test time using cost volumes. However, by using ground-truth depth supervision and provided camera poses they sidestep the challenges associated with training from self-supervision alone. [86] predict depth from triplets of frames without requiring pose information, but their method cannot deal with variable numbers of frames at test time and is trained with ground truth depth. Concurrent with our work, [85] learn depth from a cost volume, but they use stereo pairs and sparse supervised depth at training time and long sequences for pose estimation.

Most related to us are self-supervised MVS methods that also do not require any ground truth depth i.e. [46, 13]. However, there are several reasons why these existing self-supervised and supervised MVS methods aren’t applicable in many scenarios: (i) they need more than one input image at test time, (ii) they assume that the camera is not static, (iii) they typically require camera poses to be provided during training and sometimes also at test time, and (iv) they assume that there are no moving objects in the scene. Our approach leverages the best of monocular and multi-view methods by making use of sequence information at test time, when it is available, while also being robust to scene motion — see Table 1.

3. Problem setup

The aim of depth estimation is to predict a depth map $D_t$, pixel-aligned with an input image $I_t$. Conventional single-image depth estimation methods, e.g. [14, 23, 99], train a deep network $\theta_{\text{depth}}$ to map from $I_t$ to $D_t$,

$$D_t = \theta_{\text{depth}}(I_t).$$

In contrast, like other multi-frame methods [66, 81], our model accepts as input $N$ previous temporal video frames,

$$D_t = \theta_{\text{depth}}(I_{t-1}, I_{t-N}).$$

While our model makes use of information from multiple frames, it also can operate in the regime where only one frame is available at test time. Unlike similar works e.g. [50, 97, 9, 59, 5], we do not use future frames at test time e.g. $I_{t+1}$, the use of which would preclude online applications. At training time, we exploit previous and future frames as a supervisory signal, and do not require stereo supervision. We do not assume access to the true relative camera pose between $I_t$ and the preceding frames; instead we learn to predict these poses $(T_n)_{n=1}^N$ at training and test time with a differentiable pose network $\theta_{\text{pose}}$, following [99]. We also do not make use of any trained semantic models to mask moving objects e.g. [5, 26, 29]. We do, however, assume known fixed camera intrinsics $K$ — though we could relax these requirements [26, 18].

4. Method

Our method starts with two well established components: self-supervised reprojection based training, and a multi-view cost volume. We then introduce three important innovations that enable cost volume matching to work with self-supervised training from monocular video: (1) adaptive cost volumes, (2) a method to prevent a failure mode we refer to as ‘cost volume overfitting’, and (3) augmentation for static cameras and single frame inputs.

4.1. Self-supervised monocular depth estimation

Following [99], we train a self-supervision depth network using only video frames that are temporally close to $I_t$. We use the current estimated depth $D_t$ and the pose network $\theta_{\text{pose}}$’s estimate of relative camera pose $T_{t-t+n}$ to synthesize the scene from the same viewpoint as $I_t$, but only using pixels from neighboring source frames i.e. $\{I_{t+n}, n \in \{-1, 1\}\}$. The synthesized counterpart to $I_t$ is

$$I_{t+n \rightarrow t} = I_{t+n}\{\text{proj}(D_t, T_{t-t+n}, K)\},$$

where () is the sampling operator and proj returns the 2D coordinates of the depths in $D_t$ when reprojected into the camera of $I_{t+n}$. Note that while our cost volume, described later, only uses preceding frames to enable online applications, at training-time our reprojection loss uses future frames too. Following [24], for each pixel we optimize the loss for the best matching source image, by selecting the per pixel minimum over the reconstruction loss $pe$,

$$L_p = \min_n pe(I_t, I_{t+n \rightarrow t}).$$

We set $pe$ as a combination of SSIM and $L_1$ losses, and we minimize this loss over all the pixels in the training images over four output scales; see [24] for more details.

4.2. Building a cost volume

To exploit multiple input frames, inspired by [11, 42, 45] we build a cost volume which measures the geometric compatibility at different depth values between the pixels from $I_t$ and nearby source frames from the input video. This requires knowledge of relative pose $T$, which we estimate with the pose network $\theta_{\text{pose}}$, trained using a reprojection loss. We define a set of ordered planes $\mathcal{P}$, each perpendicular to the optical axis at $I_t$ and with depths linearly spaced between $d_{\text{min}}$ and $d_{\text{max}}$. Each frame is encoded into a deep feature map $F_t$ and warped to the viewpoint of $I_t$ using each of the hypothesised alternative depths $d \in \mathcal{P}$ using the known camera intrinsics and estimated pose. This creates
4.3. Adaptive cost volumes

Cost volume approaches have a problem of needing a known depth range i.e. \( d_{\min} \) and \( d_{\max} \). These are typically selected as hyperparameters in advance of training based on prior knowledge of the dataset [13] or from known camera poses [37]. We are unable to do this, as self-supervised depth estimation trained on monocular sequences only estimates depth ‘up to scale’. This means that while we assume that the final predicted depths, and corresponding poses from the pose network, will all end up in broad agreement with each other, they will be different from real-world depth by an unknown scaling factor.

To solve this problem we introduce a novel adaptive cost volume, by allowing \( d_{\min} \) and \( d_{\max} \) to be learned from the data, so they can adjust during training as the network finds its own scaling. This is done using the current predictions from the network of \( D_t \), whereby we compute the average \( \min \) and \( \max \) of each \( D_t \) over a training batch. These are then used to update an exponential moving average estimates of \( d_{\min} \) and \( d_{\max} \) with momentum 0.99. \( d_{\min} \) and \( d_{\max} \) are saved along with the model weights and then kept fixed at test time. Our approach contrasts to [27] who adapt \( d_{\min} \), \( d_{\max} \) at test time in a coarse-to-fine manner.

4.4. Addressing cost volume overfitting

We observe that our baseline cost volume model trained with monocular supervision suffers from severe artefacts, including large ‘holes’ punched on moving objects. These are similar to artefacts observed in monocular \( I_t \rightarrow D_t \) models (see [5, 24] for a description). However, in our cost volume network they are far more severe (see Fig. 3 (c)).

**Why does the monocular-trained cost volume fail?** In theory, our model should do well. It is trained with a similar reprojection loss used to train state-of-the-art single-frame depth estimators, but it also has access to an additional source of information via the cost volume. However, the information contained in the cost volume is only reliable in specific scenarios e.g. in static regions with textured surfaces. In regions where objects are moving, or where surfaces are untextured, the cost volume will be an unreliable source of depth information (Fig. 3 (b)). For example, the moving car in Fig. 3 results in a match in the cost volume at an incorrect depth and corresponds to a very low reprojection loss. During training, the network becomes over-reliant on the cost volume. Instead of ignoring the cost volume around moving objects, it trusts it too much. Artefacts in the cost volume from moving objects are then introduced in the final depth map, at both training and test time. Ultimately, the final predicted depths inherit the cost volume’s mistakes.

We introduce a method to correct this during training, by teaching the network not to trust the cost volume in these unreliable regions.

**Using a separate network to regularize.** We make the observation that single-image depth networks do not have a cost volume, so are unaffected by ‘cost volume overfitting’. While moving objects can still be a problem for these meth-
odds during training [5, 24, 69], in general they make far less severe mistakes on moving objects. We therefore use a monocular network at training time to help ‘teach’ our cost volume network the right answer — but only in regions we suspect the cost volume to be problematic. This separate network \( \theta_{\text{consistency}} \) produces a depth map \( \hat{D}_t \) for each training image, and is discarded after training. \( \theta_{\text{consistency}} \) shares \( \theta_{\text{pose}} \) with our main network to help ensure scale-consistent predictions between \( \theta_{\text{depth}} \) and \( \theta_{\text{consistency}} \). Potentially problematic pixels in our multi-frame output are identified by a binary mask \( M \). In these masked regions we apply an \( L_1 \) loss on \( \hat{D}_t \), encouraging the predictions to be similar to \( \hat{D}_t \),

\[
L_{\text{consistency}} = \sum M |D_t - \hat{D}_t|.
\]

Gradients to \( \hat{D}_t \) are blocked, ensuring knowledge only transfers from teacher to student and not vice versa.

Identifying unreliable pixels. Our binary mask \( M \) is 1 in regions considered to be unreliable, and 0 otherwise. To generate this mask we again make use of \( \hat{D}_t \). We reason that in regions where the cost volume is reliable, the depth represented by \( D_t \) will be similar to the depths represented by the argmin of the cost volume. We therefore compare the depth represented by the argmin of the cost volume (i.e. \( D_{cv} \), not \( D_t \)) to the depth \( \hat{D}_t \) predicted by \( \theta_{\text{consistency}} \). The mask \( M \) is set to 1 only in regions where \( \hat{D}_t \) and \( D_{cv} \) differ significantly, so

\[
M = \max \left( \frac{D_{cv} - \hat{D}_t}{\hat{D}_t}, \frac{\hat{D}_t - D_{cv}}{D_{cv}} \right) > 1.
\]

The idea of using a separate ‘disposable’ network to help to regularize training is not new, e.g. [69, 99]. Our novelty is in using a single-frame depth network to improve a multi-frame system. Our approach is also less costly and less constrained than using offline semantic segmentation [26], and makes fewer assumptions than RANSAC-based filtering [29]. In our experiments we compare to two alternative masking schemes from [69] and [24], and show that our approach is superior.

4.5. Static cameras and start-of-sequences

Using multiple frames at test time introduces two potential challenges for our method. The first issue is when \( I_{t-1} \) does not exist, i.e. when predicting depth for a single image or those at the start of a sequence. This case is trivially handled by monocular methods as they only require single frames as input. However, MVS approaches fail in these situations. To address this problem, during training with probability \( p \), we replace the cost volume with a tensor of zeros. For these images, this encourages the network to learn to rely only on features directly from \( I_t \). Then at test time, when \( I_{t-1} \) does not exist, we simply replace the cost volume with zeros. The second case arises when the camera does not move between \( I_{t-1} \) and \( I_t \), e.g. a car stopped at traffic lights. Again this is another failure case for MVS methods. To address this at training time, with probability \( q \), we replace the \( I_{t-1} \) input to the cost volume with a color-augmented version of \( I_t \), but still supervise with the ‘real’ \( I_{t-1}, I_{t+1} \) in Eqn. 4. This enables the network to predict plausible depths even when the cost volume is constructed from images with no camera baseline.

Our final loss is

\[
L = (1 - M)L_p + L_{\text{consistency}} + L_{\text{smooth}},
\]

where \( L_{\text{smooth}} \) is the smoothness loss from [23].

5. Implementation details

We use training-time color and flip augmentations on images being fed to the depth and pose networks, using the settings from [24]. Unless otherwise stated, all our models are trained with an input and output resolution of \( 640 \times 192 \), and we fix \( N = 1 \), so the cost volume is constructed with frames \( \{I_t, I_{t-1}\} \), at both training and test time. In all cases self-supervision during training is from frames \( \{I_{t-1}, I_t, I_{t+1}\} \). We train with Adam [47] for 20 epochs with a learning rate of \( 10^{-4} \), dropping by a factor of 10 for the final 5 epochs. After \( Q \) epochs, we fix \( \alpha_{\text{min}} \) and \( \alpha_{\text{max}} \) and the weights of \( \theta_{\text{pose}} \) and \( \theta_{\text{consistency}} \). This allows \( \theta_{\text{depth}} \) to finetune with a non-moving target. We set \( Q = 15 \) for KITTI, and \( Q = 5 \) for Cityscapes to account for the larger number of images.
in the Cityscapes training set. The feature extractor in θ_depth comprises the first five ResNet18 layers [33]. These features are aggregated into a cost volume, the result of which is concatenated with our input image features, and followed by the remaining ResNet18 convolutional layers. We use the depth decoder from [24]. Our pose network θ_pose and skip connections for θ_depth are the same as [24]. θ_consistency uses the standard architecture from [24] with no modifications. Full architecture details are in Section B. Following [24, 83, 79, 31], we use weights pretrained on ImageNet [70], but provide results trained from scratch in the supplementary material, see Table 8. For all our experiments we set p = q = 0.25 during training.

6. Experiments

Here we evaluate our ManyDepth model and (1) show that it gives SOTA results by comparing, in a standardized way, to both single-frame and multi-frame depth estimation and (2) validate our design decisions via ablations. Additional results are provided in the supplementary material.

We evaluate on two challenging depth estimation datasets, both of which exhibit moving objects. For both, we use the standard depth evaluation metrics from [14, 15].

(a) KITTI [22]. We use the Eigen split from [14]. This is commonly used for single frame depth estimation, but is more recently also used for multi-frame approaches e.g. [81, 66]. 22 frames in the KITTI Eigen test set are at the start of a sequence, and do not have a previous frame. We still include these images in the evaluation. For these images, the network does not have access to any other frames and thus makes a prediction based on one frame only. In Table 13, we additionally include models evaluated on the improved KITTI ground truth [76].

(b) Cityscapes [12]. Following [99, 90, 92], we train on 69,731 images from the monocular sequences, which we preprocess into triples using the scripts from [99]. We do not use stereo pairs or semantics. We evaluate on the 1,525 test images using the provided SGM [34] disparity maps. As with KITTI, we clip predicted depths at 80m, and only evaluate on ground truth depths less than 80m.

6.1. KITTI results

In Table 2 we compare to multi-frame approaches, some of which, e.g. [9, 5, 66, 79, 62], see more frames than ours or also use future frames e.g. [9, 5, 62]. We do not include results from [56] as they do not provide their scores on the KITTI Eigen split (see [88]). We additionally compare to the best-performing self-supervised monocular depth estimation approaches. To control for resolution, we separate low and high resolution models, and we also split methods which use expensive multi-pass test-time refinement into separate sections. We observe that our approach outperforms all previously published self-supervised methods that do not use semantic supervision on most metrics. We also
implement the test-time refinement scheme of [62] on our model, updating the weights of the depth and pose encoders using sequential pairs of images from the test set, for 50 steps. Not surprisingly, this further improves our results, and we outperform other test-time refinement methods.

Qualitative results are presented in Fig. 4. In some cases the predicted depth maps looks qualitatively similar to the monocular only models, but the error maps show the high magnitude of mistakes which can be present.

**Efficiency comparison.** Fig. 5 illustrates the runtime efficiency of our ManyDepth models (640 x 192: ◆ and 1024 x 320: ◆, ◆) compared to other methods, including test-time refinement approaches (X). We report multiply-add computations (MACs) for each method and show that test-time refinement models which perform multiple forward-backward passes are too computationally demanding for use in real-time applications. See Table 11 for a full results table, and Section C for additional details.

### 6.2. KITTI ablation

In Table 4 we show the importance of the various components of our approach by turning them on and off in turn. **ManyDepth w/o motion masking:** We omit Lconsistency from our loss and set M to zeros everywhere.

**ManyDepth w/o motion masking, w/o augmentation:** As above, but also omitting our augmentations.
ManyDepth with motion masking but no teacher: We remove $L_{\text{consistency}}$ but still use $M$ to mask $L_p$.

Stack of 2 frames as input: A baseline which directly maps $(I_{t-1}, I_t)$ to $D_t$. We modify [24]'s network to accept two images as input, and train using their loss.

ManyDepth with motion masking from [69]: We use our full loss, but our mask $M$ is the same as [69]. We use their pretrained models to compute these masks offline for the entire training set.

ManyDepth with motion masking from [24]: Here we use our full loss, but set the mask $M$ to an ‘automask’ from [24].

Khot et al. [46]: We trained this unsupervised MVS approach on KITTI, with the implementation from [30].

ManyDepth $(I_{t-2}, I_{t-1}, I_t)$ and ManyDepth $(I_{t-1}, I_t, I_{t+1})$: Retrained variants of our model which build the cost volume from three frames instead of just two. This improves some metrics but not all.

Benefit of our augmentations. In Table 5 we evaluate three different scenarios, comparing our model to a baseline which was trained without our augmentations from Section 4.5. When evaluating in ‘standard’ mode (i.e. using the previous and current frames as input) on the entire KITTI test set, the difference between the two models is negligible. This is partially because the KITTI test images are predominately from a moving camera. However, when we evaluate in ‘start-of-sequence’ mode (i.e. the standard monocular setting using only $(I_t)$ as input) and ‘static camera’ evaluation mode (i.e. simulating a static camera with inputs $(I_t, I_{t+1})$), our augmentation scheme is significantly better.

6.3. Cityscapes results

In Table 3 we perform additional comparisons where we train and test on the Cityscapes dataset [12]. Again, we consistently outperform competing methods, even those that use semantic supervision.

7. Conclusion

We presented a fully self-supervised online method that predicts superior depths from a single image, or from multiple images when they are available. We achieve the benefits of both multi-frame and monocular methods, while being more robust on moving objects and static cameras compared to a naive integration of a cost volume. We presented state-of-the-art results on both the KITTI and Cityscapes datasets. While test-time refinement methods are close competitors in terms of depth accuracy, we have shown that our method is significantly more efficient during inference. We expect that our results could be further improved via recent complimentary advances in monocular depth estimation e.g. discretized output depths [25] or feature based losses [72].

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References

[1] Filippo Aleotti, Fabio Tosi, Li Zhang, Matteo Poggi, and Stefano Mattoccia. Reversing the cycle: self-supervised deep stereo through enhanced monocular distillation. In ECCV, 2020.

[2] V Madhu Babu, Kaushik Das, Anima Majumdar, and Swagat Kumar. Undemon: Unsupervised deep network for depth and ego-motion estimation. In IROS, 2018.

[3] Jiawang Bian, Zhichao Li, Naiyan Wang, Huangying Zhan, Chunhua Shen, Ming-Ming Cheng, and Ian Reid. Unsupervised scale-consistent depth and ego-motion learning from monocular video. In NeurIPS, 2019.

[4] Michael Bloesch, Jan Czarnowski, Ronald Clark, Stefan Leutenegger, and Andrew J Davison. CodeSLAM—learning a compact, optimisable representation for dense visual SLAM. In CVPR, 2018.

[5] Vincent Casser, Soeren Pirk, Reza Mahjourian, and Anelia Angelova. Depth prediction without the sensors: Leveraging structure for unsupervised learning from monocular videos. In AAAI, 2019.

[6] Vincent Casser, Soeren Pirk, Reza Mahjourian, and Anelia Angelova. Unsupervised monocular depth and ego-motion learning with structure and semantics. In CVPR Workshops, 2019.

[7] Jia-Ren Chang and Yong-Sheng Chen. Pyramid stereo matching network. In CVPR, 2018.

[8] Weifeng Chen, Zhao Fu, Dawei Yang, and Jia Deng. Single-image depth perception in the wild. In NeurIPS, 2016.

[9] Yuhua Chen, Cordelia Schmid, and Cristian Sminchisescu. Self-supervised learning with geometric constraints in monocular video: Connecting flow, depth, and camera. In ICCV, 2019.

[10] Xinjing Cheng, Peng Wang, and Ruigang Yang. Learning depth with convolutional spatial propagation network. PAMI, 2019.

[11] Robert T Collins. A space-sweep approach to true multi-view matching. In CVPR, 1996.

[12] Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. The cityscapes dataset for semantic urban scene understanding. In CVPR, 2016.

[13] Yuchao Dai, Zhidong Zhu, Zhibo Rao, and Bo Li. MVS$: Deep unsupervised multi-view stereo with multi-view symmetry. In 3DV, 2019.

[14] David Eigen and Rob Fergus. Predicting depth, surface normals and semantic labels with a common multi-scale convolutional architecture. In ICCV, 2015.

[15] David Eigen, Christian Puhrsch, and Rob Fergus. Depth map prediction from a single image using a multi-scale deep network. In NeurIPS, 2014.

[16] Jakob Engel, Thomas Schöps, and Daniel Cremers. LSD-SLAM: Large-scale direct monocular slam. In ECCV, 2014.

[17] José M Fácil, Alejo Concha, Luis Montesano, and Javier Civera. Single-view and multi-view depth fusion. IEEE Robotics and Automation Letters, 2017.

[18] Jose M Facil, Benjamin Ummenhofer, Huizhong Zhou, Luis Montesano, Thomas Brox, and Javier Civera. CAM-Convs: Camera-aware multi-scale convolutions for single-view depth. In CVPR, 2019.

[19] Philipp Fischer, AlexeyDosovitskiy, Eddy Ilg, Philip Häusser, Caner Hazrdbaş, Vladimir Golkov, Patrick van der Smagt, Daniel Cremers, and Thomas Brox. FlowNet: Learning optical flow with convolutional networks. In ICCV, 2015.

[20] Huan Fu, Mingming Gong, Chaohui Wang, Kayhan Batmanghelich, and Dacheng Tao. Deep ordinal regression network for monocular depth estimation. In CVPR, 2018.

[21] Ravi Garg, Vijay Kumar BG, and Ian Reid. Unsupervised CNN for single view depth estimation: Geometry to the rescue. In ECCV, 2016.

[22] Andreas Geiger, Philip Lenz, and Raquel Urtasun. Are we ready for Autonomous Driving? The KITTI Vision Benchmark Suite. In CVPR, 2012.

[23] Clément Godard, Oisin Mac Aodha, and Gabriel J Brostow. Unsupervised monocular depth estimation with left-right consistency. In CVPR, 2017.

[24] Clément Godard, Oisin Mac Aodha, Michael Firman, and Gabriel J. Brostow. Digging into self-supervised monocular depth estimation. In ICCV, 2019.

[25] Juan Luis Gonzalez and Munchurl Kim. Forget about the LiDAR: Self-supervised depth estimators with MED probability volumes. NeurIPS, 2020.

[26] Ariel Gordon, Hanhan Li, Rico Jonschkowski, and Anelia Angelova. Depth from videos in the wild: Unsupervised monocular depth learning from unknown cameras. In ICCV, 2019.

[27] Xiaodong Gu, Zhiwen Fan, Siyu Zhu, Zuoicuii Dai, Feitong Tan, and Ping Tan. Cascade cost volume for high-resolution multi-view stereo and stereo matching. In CVPR, 2020.

[28] Vitor Guizilini, Rares Ambrus, Sudeep Pillai, Allan Rava-tos, and Adrien Gaidon. 3D packing for self-supervised monocular depth estimation. In CVPR, 2020.

[29] Vitor Guizilini, Rui Hou, Jie Li, Rares Ambrus, and Adrien Gaidon. Semantically-guided representation learning for self-supervised monocular depth. In ICLR, 2020.

[30] Xiaoyang Guo. PyTorch implementation of MVS-Net. https://github.com/xy-guo/MVSNet_pytorch, 2020.

[31] Xiaoyang Guo, Hongsheng Li, Shuai Yi, Jimmy Ren, and Xiaogang Wang. Learning monocular depth by distilling cross-domain stereo networks. In ECCV, 2018.

[32] Hyowon Ha, Sunghoon Im, Jaesik Park, Hae-Gon Jeon, and In So Kweon. High-quality depth from uncalibrated small motion clip. In CVPR, 2016.

[33] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In CVPR, 2016.

[34] Heiko Hirschmuller. Stereo processing by semiglobal matching and mutual information. PAMI, 2007.

[35] Yuxin Hou, Juho Kannala, and Arno Solin. Multi-view stereo by temporal nonparametric fusion. In ICCV, 2019.
[73] Nikolai Smolyanskiy, Alexey Kamenev, and Stan Birchfield. On the importance of stereo for accurate depth estimation: An efficient semi-supervised deep neural network approach. In CVPR Workshops, 2018.

[74] Keisuke Tateno, Federico Tombari, Iro Laina, and Nassir Navab. Cnn-slam: Real-time dense monocular slam with learned depth prediction. In CVPR, 2017.

[75] Fabio Tosi, Filippo Alcotti, Pierluigi Zama Ramirez, Matteo Poggi, Samuele Salti, Luigi Di Stefano, and Stefano Mattoccia. Distilled semantics for comprehensive scene understanding from standing videos. In CVPR, 2020.

[76] Jonas Uhrig, Nick Schneider, Lukas Schneider, Uwe Franke, Thomas Brox, and Andreas Geiger. Sparsity invariant CNNs. In 3DV, 2017.

[77] Benjamin Ummenhofer, Huizhong Zhou, Jonas Uhrig, Niklaus Mayer, Eddy Ilg, Alexey Dosovitskiy, and Thomas Brox. DeMoN: Depth and motion network for learning monocular stereo. In CVPR, 2017.

[78] Sudheendra Vijayanarasimhan, Susanna Ricco, Cordelia Schmid, Rahul Sukthankar, and Katerina Fragkiadaki. SFM-Net: Learning of structure and motion from video. arXiv:1704.07804, 2017.

[79] Jianrong Wang, Ge Zhang, Zhenyu Wu, XueWei Li, and Li Liu. Self-supervised joint learning framework of depth estimation via implicit cues. arXiv:2006.09876, 2020.

[80] Zhenheng Yang, Peng Wang, Yang Wang, Wei Xu, and Ram Nevatia. LEGO: Learning edge with geometry all at once by watching videos. In CVPR, 2018.

[81] Haokui Zhang, Chunhua Shen, Ying Li, Yuanzhi Niu, and Youliang Yan. Exploiting temporal consistency for real-time video depth estimation. In ICCV, 2019.

[82] Tinghui Zhou, Matthew Brown, Noah Snavely, and David Lowe. Unsupervised learning of depth and ego-motion from video. In CVPR, 2017.
**Supplementary Material**

A. Additional Qualitative Results

**YouTube videos.** We use our model trained on KITTI to make predictions on frames from a YouTube video, downloaded from the Wind Walk Travel Videos channel. We include some of these predictions in Figure 6 to demonstrate the ability of our KITTI-trained model to transfer between different datasets. We also include predictions from an equivalent KITTI-trained Monodepth2 model [24]. This monocular only baseline fails to pick out some of the details, as it cannot take advantage of the multiple test-time viewpoints.

**KITTI dataset.** Additional qualitative results on the KITTI dataset are shown here in Figures 8, 9, and 10. Ground truth depth maps and the error maps use the improved, densified, ground truth from [76]. We also show a colorbar for the error maps in Figure 7. The error maps show the absolute relative error in depth, computed as

\[
\text{abs\_rel\_error} = \frac{|D_{\text{pred}} - D_{\text{gt}}|}{D_{\text{gt}}},
\]

B. Architecture details

Here we describe the architecture of our model. Unless otherwise specified, we use a ResNet18 [33] as the basis for our depth network. See Figure 2 from the main paper for a graphical depiction. Our feature extractor evaluates up until the output of the first residual layer of the ResNet18, resulting in a tensor which is a quarter of the input resolution with 64 channels. These features are then aggregated into a cost volume for each input frame and the resulting features are combined in the cost volume.

A full description of our architecture is in Table 6. Finally, our consistency network \(\theta_{\text{consistency}}\) uses the standard architecture from [24] with no additional modifications.

C. Efficiency computations

In Table 11 we show the computations used to generate the graph in Figure 5 in the main paper. Multiply-add computations (MACs) were generated with the THOP library

\[\text{https://github.com/Lyken17/pytorch-OpCounter}\]
Figure 6. **Qualitative results on YouTube videos.** All predictions are made with a model trained on the KITTI dataset. Note how our method is able to correctly estimate the shape of the sign in the top row, the car on the left in the second row, the pillars in the third row, and the signs in the fourth and fifth rows.

**D.2. Models trained from scratch**

Table 8 shows KITTI results trained without ImageNet pretraining. Scores are slightly worse than our ‘with pretraining’ results, but are still competitive.

**D.3. Additional KITTI ablation scores**

In Table 7 we show full metrics for ablations, performed on the KITTI Eigen test set. These experiments are described in detail in the main paper. We note that while the motion masking method of [24] is competitive with our approach on KITTI, we show in our Cityscapes ablations (Table 9) how, when more moving objects are present, our masking scheme is significantly better than that of [24].

**D.4. Full scores for augmentation ablation**

Table 10 we show the full set of metrics for the experiment described in Section 6.2 of the main paper, and presented in Table 4 of the main paper.
E. Additional results on Cityscapes dataset

E.1. Alternative crop evaluation schemes

Past literature has used different cropping schemes for evaluating on the Cityscapes dataset. In Table 12 we show our Cityscapes results, evaluated with these two different schemes:

**Evaluation cropping scheme ‘A’**: Here, we crop the center 50% of pixels vertically, reducing the image size from $2048 \times 1024$ to $2048 \times 512$. Next we remove a 192 pixels from the left and the right of the image, giving a final evaluation region of $1664 \times 512$. This is the evaluation scheme used by [6, 53, 26], following conversations with the authors.

**Evaluation cropping scheme ‘B’**: Here, we only evaluate the top 75% of the image, ignoring the bottom 25% of pixels. This leaves an evaluation region of size $2048 \times 768$. This effectively crops out the ‘car’ from the bottom of the image. This evaluation method is the suitable for evaluating works which also train with this same cropping scheme, e.g. [99, 90, 92].

E.2. Cityscapes ablation

In Table 9 we show an ablation of our masking schemes on Cityscapes [12], mirroring similar experiments on KITTI in the main paper. Again we see that our contributions help. We do not use the masking scheme of [69], as they do not provide trained models on Cityscapes. The improvements that our masking provides, compared to the baselines and [24], is superior on this dataset compared with KITTI. Cityscapes contains more moving objects, so benefits more from our training scheme.

F. Note on Cityscapes training of Monodepth2

In Table 3 of the main paper, we show the scores on the Cityscapes dataset for our implementation of Monodepth2 [24]. To obtain these, we trained for 5 epochs with a batch size of 12, mirroring the training procedure of our consistency network. This is to account for the far larger number of images in the Cityscapes training dataset compared to KITTI. We note that when trained for a full 20 epochs, the resulting scores are significantly worse.

![Color scale used for all error plots in the paper, supplementary material, and video. Values on the color axis are units of absolute relative error, applied after median scaling of the predicted depth. See Eqn. 7 for details on how to compute this error.](image-url)
Figure 8. **Further qualitative results on the KITTI dataset (part 1)**. Error maps on the right measure the absolute relative error compared to the ground truth, after median scaling [14]. Errors range from blue (low error, abs. rel. = 0.0) to red (high error, abs. rel. = 0.2). The color mapping in all error maps are the same, and the colorbar is shown in Figure 7.
Figure 9. **Further qualitative results on the KITTI dataset (part 2).** Error maps on the right measure the absolute relative error compared to the ground truth, after median scaling [14]. Errors range from blue (low error, abs. rel. = 0.0) to red (high error, abs. rel. = 0.2). The color mapping in all error maps are the same, and the colorbar is shown in Figure 7.
| Ablation | Abs Rel | Sq Rel | RMSE  | RMSE log | δ < 1.25 | δ < 1.25² | δ < 1.25³ |
|----------|---------|--------|-------|----------|----------|----------|----------|
| ManyDepth full | 0.098 | 0.770 | 4.459 | 0.176 | 0.900 | 0.965 | 0.983 |
| ManyDepth (w/o motion masking) | 0.113 | 1.354 | 5.228 | 0.196 | 0.885 | 0.956 | 0.978 |
| ManyDepth (w/o motion masking, w/o augmentation) | 0.284 | 11.240 | 8.516 | 0.297 | 0.813 | 0.896 | 0.934 |
| ManyDepth (with motion masking but no teacher) | 0.154 | 2.682 | 6.573 | 0.236 | 0.842 | 0.933 | 0.965 |
| Stack of 2 frames as input | 0.121 | 1.028 | 5.016 | 0.198 | 0.868 | 0.956 | 0.979 |
| ManyDepth (with motion masking from [69]) | 0.099 | 0.783 | 4.447 | 0.176 | 0.899 | 0.964 | 0.983 |
| ManyDepth (with motion masking from [24]) | 0.099 | 0.780 | 4.465 | 0.178 | 0.899 | 0.963 | 0.982 |
| ManyDepth with 3-frame input (-2, -1, 0) | 0.098 | 0.780 | 4.430 | 0.176 | 0.902 | 0.964 | 0.983 |
| ManyDepth with 3-frame input (-1, 0, +1) | 0.097 | 0.768 | 4.431 | 0.175 | 0.900 | 0.964 | 0.983 |

Table 7. **Full metrics from KITTI 2015 ablation (Table 4 in the main paper).** Here we ablate our method on KITTI 2015 [22] using the Eigen split, reporting all seven metrics. Details for these experiments are given in the main paper.

| Ablation | Abs Rel | Sq Rel | RMSE  | RMSE log | δ < 1.25 | δ < 1.25² | δ < 1.25³ |
|----------|---------|--------|-------|----------|----------|----------|----------|
| Monodepth2 HR (no pt)† | 0.131 | 1.063 | 5.112 | 0.208 | 0.851 | 0.950 | 0.977 |
| Ours HR (no pt) | 0.104 | 0.844 | 4.598 | 0.185 | 0.889 | 0.959 | 0.981 |
| Monodepth2 HR | 0.115 | 0.882 | 4.701 | 0.190 | 0.879 | 0.961 | 0.982 |
| Ours HR | 0.093 | 0.715 | 4.245 | 0.172 | 0.909 | 0.966 | 0.983 |

Table 8. **Comparing the effect of ImageNet pretraining on the KITTI 2015 depth dataset.** For most of our experiments we follow [24, 83, 79, 31] etc. in using weights pretrained on ImageNet. As expected, pretraining improves scores, but we are still extremely competitive without it. † is trained by us using the authors’ code.

| Ablation | Abs Rel | Sq Rel | RMSE  | RMSE log | δ < 1.25 | δ < 1.25² | δ < 1.25³ |
|----------|---------|--------|-------|----------|----------|----------|----------|
| ManyDepth (w/o motion masking) | 0.185 | 4.080 | 8.499 | 0.240 | 0.803 | 0.921 | 0.960 |
| ManyDepth (with motion masking from [24]) | 0.143 | 2.300 | 7.073 | 0.199 | 0.844 | 0.951 | 0.977 |
| ManyDepth full | 0.114 | 1.193 | 6.223 | 0.170 | 0.875 | 0.967 | 0.989 |

Table 9. **Ablation on the Cityscapes dataset.** Here we ablate our method on the Cityscapes dataset, evaluating as described in the main paper. Our motion masking contributions make significantly larger improvements on Cityscapes compared to KITTI, as more moving objects are present in the Cityscapes training and test footage.

| Test-time input | Model | Abs Rel | Sq Rel | RMSE  | RMSE log | δ < 1.25 | δ < 1.25² | δ < 1.25³ |
|-----------------|-------|---------|--------|-------|----------|----------|----------|----------|
| Standard: \((I_{t-1}, I_t)\) | No augmentation | 0.100 | 0.794 | 4.432 | 0.179 | 0.895 | 0.962 | 0.982 |
| | ManyDepth | 0.098 | 0.770 | 4.459 | 0.176 | 0.900 | 0.965 | 0.983 |
| Start-of-sequence: \((I_t)\) | No augmentation | 0.115 | 0.903 | 4.863 | 0.193 | 0.877 | 0.959 | 0.981 |
| | Monodepth [24] | 0.148 | 1.076 | 5.161 | 0.219 | 0.812 | 0.943 | 0.977 |
| | ManyDepth | 0.118 | 0.892 | 4.764 | 0.192 | 0.871 | 0.959 | 0.982 |
| Static camera: \((I_t, I_t)\) | No augmentation | 0.158 | 1.132 | 5.228 | 0.225 | 0.794 | 0.939 | 0.977 |
| | ManyDepth | 0.117 | 0.886 | 4.754 | 0.191 | 0.872 | 0.959 | 0.982 |

Table 10. **Full metrics for ‘our augmentations help’ (Table 5 in main paper).** We compare two variants of our model, one trained with our novel data augmentations (‘Ours’) and one without. We create two artificial scenarios to test each model’s performance on start-of-sequence images (where we just input \(I_t\)) and static cameras (where both input frames are the exact same).
Table 11. Details on multiply-add computations (MACs) calculations. For our multi-frame model, ‘Encoder’ MACs includes performing feature extraction for both inputs frames, creating the cost volume and performing the final ResNet18 encoder layers. See text for more details.

Table 12. Results on Cityscapes. Our method beats all competing models. † is trained by us using the authors’ code, with the data preprocessing from [99]. See Section E.1 for more details. The two alternative cropping evaluation schemes ‘A’ and ‘B’ are described in the text. Numbers from Pilzer et al. [67] are from their Half-Cycle Mono variant, which is the only one of their models which does not rely on access to stereo pairs at test time.

Table 13. KITTI [22] evaluation on improved ground truth from [76], as described in [24]. As in the main paper, at top we compare medium and low resolution results without and with test-time refinement (TTR). At bottom we compare high resolution results without and with TTR. Best results in each subsection are in bold. Our method outperforms all previous methods in all subsections across all metrics, whether or not the baselines use multiple frames at test time. We don’t report results on the new ground truth using the methods [62, 5, 6, 26, 29, 9, 59, 72] as they were not reported in the publications, and the raw predictions have not been made public by the authors. None of the methods presented here were trained with semantics. **Legend:** TTR – Uses test-time refinement  Semantics – Semantic supervision  † – evaluated on whole sequences
Figure 10. **Further qualitative results on the KITTI dataset (part 3).** Error maps on the right measure the absolute relative error compared to the ground truth, after median scaling [14]. Errors range from blue (low error, abs. rel. = 0.0) to red (high error, abs. rel. = 0.2). The color mapping in all error maps are the same, and the colorbar is shown in Figure 7.