Semi-Supervised Learning of Monocular Depth Estimation via Consistency Regularization with K-way Disjoint Masking

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Abstract

Semi-Supervised Learning (SSL) has recently accomplished successful achievements in various fields such as image classification, object detection, and semantic segmentation, which typically require a lot of labour to construct ground-truth. Especially in the depth estimation task, annotating training data is very costly and time-consuming, and thus recent SSL regime seems an attractive solution. In this paper, for the first time, we introduce a novel framework for semi-supervised learning of monocular depth estimation networks, using consistency regularization to mitigate the reliance on large ground-truth depth data. We propose a novel data augmentation approach, called $K$-way disjoint masking, which allows the network for learning how to reconstruct invisible regions so that the model not only becomes robust to perturbations but also generates globally consistent output depth maps. Experiments on the KITTI and NYU-Depth-v2 datasets demonstrate the effectiveness of each component in our pipeline, robustness to the use of fewer and fewer annotated images, and superior results compared to other state-of-the-art, semi-supervised methods for monocular depth estimation. Our code is available at https://github.com/KUCVLAB/MaskingDepth.

1. Introduction

Monocular depth estimation, which aims at estimating a dense depth map from a single image, has been one of the most essential computer vision tasks and can be useful in many fields such as Augmented Reality (AR) [45], Virtual Reality (VR) [33], and autonomous driving [39, 78].

As a pioneering work, Eigen et al. [21] introduced a deep learning-based approach for this task, and several works [37, 46, 66] based on a supervised learning regime have achieved higher and higher accuracy through the years. However, such a learning paradigm requires a large number of images and corresponding ground-truth dense depths, which are notoriously challenging to obtain [25, 59]. To overcome this, self-supervised learning techniques [28, 29, 82], which formulate monocular depth estimation as an image reconstruction problem, have been popularly proposed. However, these self-supervised methods often require extra data, such as stereo pairs or video sequences [29, 82] which are not always available. In addition, they are known to suffer from scale ambiguity problems and often result in blurred depth at object boundaries and missing instances [5, 14].

On the other hand, to mitigate the reliance on large amounts of labeled data, methods in other fields such as image classification [44, 57, 60] and semantic segmentation [22, 50] have attempted to develop semi-supervised learning frameworks to leverage unlabeled data. Recent successful strategies [8, 60, 62] showed promising performance given very restricted labeled data accompanied with an abundant amount of unlabeled data. Among them, FixMatch [60] and PseudoSeg [83] in particular showed impressive results by utilizing consistency regularization, a technique that encourages results of strongly-augmented unlabeled data to follow pseudo labels obtained from weakly-augmented unlabeled data.

Compared to other annotations such as image class labels [60] and segmentation labels [83], the cost of obtaining and refining the depth map is much higher and would motivate the need for such techniques, but there has not yet been an attempt to apply SSL approaches for monocular depth estimation. Indeed, adopting the consistency regularization framework to monocular depth estimation is non-trivial. To implement consistency regularization, proper data augmentation is essential, but depth-specific augmentations have rarely been studied [36], and existing techniques have not shown significant effectiveness for monocular depth estimation [34, 36].

In this paper, for the first time, we present a novel semi-
supervised learning framework for monocular depth estimation based on consistency regularization. To apply enough perturbations to an input image in a consistency regularization framework, we propose to adopt a token masking technique as data augmentation, inspired by recent Masked Image Modeling (MIM) strategies for Transformers [6, 32, 74]. Even though MIM yielded superior performance on some tasks, such as image classification and semantic segmentation, naively adopting this as an augmentation technique may increase inherent ambiguity [9, 52] when we estimate the depth of the masked tokens. To overcome this, we present a new approach called K-way disjoint masking as augmentation, where K-disjoint sets of tokens are encoded independently, then concatenated and decoded simultaneously, which helps to generate reliable depth maps while keeping the beneficial effects of masking-based data augmentation. In our framework, we encourage depth and feature consistencies [6] across two branches from two augmented views by K-way disjoint masking. In addition, uncertainty estimation [35, 55] is also jointly modeled to aid the depth consistency and facilitate the convergence of training.

In experiments, we evaluate our framework on standard benchmarks, including KITTI [25] and NYU-Depth-v2 [59]. Our framework shows outstanding performance compared to other semi-supervised monocular depth estimation methods. Especially, our proposed method retains stable performance on sparser label settings. In addition, we show that the proposed K-way disjoint masking is effective as an augmentation technique and validate each component through an extensive ablation study.

2. Related Work

Monocular Depth Estimation. Monocular depth estimation aims at estimating a depth from a single image. [21] pioneered work tackled this task with deep neural networks. Since then, several approaches [46, 66] based on supervised learning, i.e., utilizing ground-truth labels, have been presented to improve performance. Although these methods have achieved remarkable accuracy over traditional, hand-crafted approaches [43, 58], their success depends on massive amounts of ground-truth depth maps that require a labor-intensive process for collection and cleaning [25, 59].

To address this limitation, self-supervised learning methods [24, 29, 72] formulate the task as an image reconstruction, leveraging geometric information over stereo pairs or a sequence of frames. These approaches have emphasized the importance to mitigate the dependency on annotations. However, they often suffer from blurred results [14] and scale inconsistencies when using videos [67, 68]. Unlike both of the aforementioned approaches, there has not been much work on semi-supervised depth estimation. [42] simply combined supervised and self-supervised loss functions and [2] utilized a left-right consistency to improve performance. Recently, several works [13, 31, 64, 71] have attempted to use stereo knowledge to distill labels for monocular depth estimation. Although they seem to be attractive solutions, they are still constrained by the need for specific data (stereo pairs) and additional computation costs (training a stereo module). Our proposed framework alleviates the reliance on labeled data by leveraging consistency regularization which allows us to use unlabeled data.

Semi-supervised Learning. Semi-supervised learning (SSL) [44, 60, 73] has recently emerged as an important area in deep learning. Since collecting labeled data is time-consuming, SSL is a powerful approach to train models on a few annotated samples accompanied by a large amount of unlabeled data. Consistency regularization [3, 44, 57] is one of the commonly used strategies for SSL. It leverages unlabeled data by relying on the assumption that the model
outputs should be consistent when perturbations are either applied or not to input samples. Recently, numerous methods [7, 60, 73] that utilize a weakly-augmented image to generate a pseudo-label and enforce consistency against the strongly-augmented image have been proposed. SSL approaches are also used for semantic segmentation [22, 83] to utilize unlabeled data. Inspired by the success of the SSL regime in other fields, we propose a novel semi-supervised framework for monocular depth estimation.

**Masked Image Modeling.** Masked image modeling is the process of learning representations by reconstructing images that are corrupted by masking [6, 32, 74]. After BERT [17] proposed the masked language modeling tasks, which is one of the successful methods for pre-training in NLP, related works explored a variety of masked image predictions strategies suited for Transformers [6, 32]. ViT [19] studies a masked patch prediction to learn the representation, and BEIT [6] proposes to predict discrete tokens. Recent literature [32, 74] introduce an extremely simple yet effective approach, called masked autoencoder (MAE). MAE [32] only utilizes unmasked tokens to encode meaningful representations. In addition, MRA [75] leverages this strategy to generate augmented images. In this paper, we propose an effective data augmentation strategy tailored for consistency regularization.

### 3. Methodology

#### 3.1. Motivation and Overview

Let us denote a color image and its corresponding depth map as $I$ and $D$, respectively. The objective of monocular depth estimation is to learn a mapping function $f$ from the image $I$ to its corresponding depth $D$ such that $D = f(I)$. Recent learning-based methods formulate the mapping function with convolutions [21, 37, 69] or Transformers [47, 56, 76] as a network $f_\theta$ with parameters $\theta$. To train the monocular depth estimation networks $f_\theta$ in a supervised manner, the ground-truth $D_{gt}(i)$ defined for all pixels $i$ is required, but building large-scale dense depth data is notoriously challenging [24, 72]. In addition, to alleviate depth capture errors, post-processing [25, 59, 65] is essential.

To overcome this reliance on labeled data, many recent approaches [11, 24, 53, 71, 77, 82] proposed unsupervised or self-supervised learning frameworks, casting the task as an image synthesis problem. Although such self-supervised learning processes mitigate the reliance on labeled data, it often results in blurring results around depth boundaries and failure at accounting for occluded pixels [1, 28]. In addition, it also requires the dataset to consist of stereo pairs or a sequence of frames, which are not always available [25, 59]. In order to combine the complementary advantages of supervised and self-supervised methods, semi-supervised approaches such as combining the two [31, 42] or stereo knowledge distillation [13, 63] have been studied. However, they also have limitations, since posing constraints on the training data composition – needing stereo pairs or sequence images – and additional computation costs for training stereo networks.

In this paper, we present a novel semi-supervised learning framework for learning monocular depth estimation on a large number of unlabeled images with sparsely depth-annotated data. As shown in Fig 1, following recent trends of semi-supervised learning [8, 41, 60, 62], we introduce for the first time consistency regularization between two dif-
further augmented views from the same image to train the monocular depth estimation network. However, it is challenging to directly apply the existing consistency regularization techniques [44, 49, 57] due to the absence of effective data augmentation for monocular depth estimation. To deal with this, we reformulate this paradigm for our purposes as follows.

### 3.2. Formulation

Given image $I$, we formulate two different branches, one for processing images passed through weak augmentation (called weak branch) and the other for images strongly augmented (called strong branch), where the consistency between the two images through the networks $f_\theta$ is encouraged. In particular, a weakly-augmented image $I_{\text{weak}}$ and a strongly-augmented image $I_{\text{strong}}$ are fed to the network $f_\theta$, and then consistency is defined as follows:

$$
\mathcal{L} = \mathcal{R}(\text{stopgrad}(f_\theta(I_{\text{weak}})), f_\theta(I_{\text{strong}})),
$$

where $\text{stopgrad}(\cdot)$ is a stop-gradient operation and $\mathcal{R}(\cdot, \cdot)$ is a distance function, e.g., mean squared error (MSE) [70] or KL-divergence [38]. In this setting, we can interpret $f_\theta(I_{\text{weak}})$ as a pseudo ground-truth. To effectively implement this strategy, differences between prediction results of divided branches should be made through conventional data augmentation techniques such as crop [18] or rotation [27] which are successfully used in consistency regularization for image classification.

In this framework (as illustrated in Fig 2), following recent successes [56], we consider the backbone model $f_\theta$ consisting of a Transformer-based encoder $f_\theta^{\text{enc}}$, which takes a tokenized image as input and outputs the encoded features [19], and a CNN-based decoder $f_\theta^{\text{dec}}$. However, in monocular depth estimation, if we apply conventional data augmentation techniques such as unconstrained crop [18] or rotation [27], geometric inconsistency due to inherent scale ambiguity emerges, and thus the consistency regularization cannot be properly established for our purpose.

To address this issue, we present a novel data augmentation technique tailored to monocular depth estimation, inspired by recent masked image modeling techniques [4, 32, 74], which allows for generating geometrically consistent pseudo depth maps while applying sufficient perturbations to the inputs. In our framework, we encourage not only feature similarities [6] but also depth similarities between the two branches processing the two augmented views, where the latter is aided by uncertainty estimation [35, 55] to ease the convergence of training.

### 3.3. K-way Disjoint Masking

In this section, we explain how to apply the proposed data augmentation strategy which we call K-way disjoint masking, tailored for consistency regularization in monocular depth estimation. Our key ingredient is inspired by recent MIM techniques for Transformers [6, 32, 74]. The most naive way to formulate this consists of simply masking out the tokens. Specifically, given an image $I \in \mathbb{R}^{h \times w \times 3}$, we reshape it into a sequence of flattened non-overlapped 2D patches $X \in \mathbb{R}^{N \times P}$, where $h \times w$ is the resolution of the original image, $P = p \times p \times 3$ and $p \times p$ is the resolution of each image patch, and $N = hw/p^2$. These flattened 2D patches $X$ are embedded by a trainable linear projection [19] operator, which proceeds to be fed into the Transformer encoder $f_\theta^{\text{enc}}$. By applying the randomly sampled mask, the sequence of flattened 2D patches $X$ can be transformed into $X'$. Note that similar techniques were also used to increase the robustness of Transformers for image-level or pixel-level classification such as segmentation [32, 74]. However, adopting a naive masking strategy for monocular depth estimation is not effective, as we could observe that continuous depth map generation for regions missing
from neighboring tokens yields blurred results [52] due to increasing, inherent ambiguity.

To address this, we present a K-way disjoint masking technique, where a K-disjoint set of tokens are encoded independently, then concatenated and decoded simultaneously, as illustrated in Fig 3. Since our method eventually captures the entire scene from the partially divided inputs, it can get deterministic results by reducing inherent ambiguity [52]. Moreover, since it enforces scale consistency by keeping the image size and orientation unaltered, the K-disjoint masking strategy can also act as data augmentation. Specifically, we divide the sequence of flattened 2D patches $X \in \mathbb{R}^{N \times P}$ into K non-overlapping subsets $X_k$ for $k \in \{1, ..., K\}$, with $X_k \in \mathbb{R}^{M \times P}$, where $M$ is set to be a random value smaller than $N$ to avoid learning with a fixed size of the tokens set. In other words, the concatenation of all the $X_k$ tokens should reconstruct the original token representation $X$, while keeping the proper position ordering such that

$$X = [X_1, X_2, ..., X_K],$$  \hspace{1cm} (2)

where $[\cdot]$ denotes a concatenation operator. By independently encoding $X_k$ to the latent vector $z_k$ such that $z_k = f_{\theta}^\text{enc}(X_k)$, unlike original Transformer-based encoding, i.e., $z = f_{\theta}^\text{enc}(X)$, the limited candidates are considered when running self-attention computation, which in turn implements an augmentation over tokens. Then, to decode all the $z_k$, we reassemble them as $Z = [z_1, z_2, ..., z_K]$ and obtain the final depth map as $D = f_{\theta}^\text{dec}(Z)$.

In our framework, by adjusting $K$, we act on the intensity of augmentations to the networks. In our experiments, we empirically set $K = 1$ for the weak branch, and $K = 64$ for the strong branch, which generate decoded depth maps $D_{\text{weak}}$ and $D_{\text{strong}}$, respectively.

### 3.4. Loss Functions

To train the networks we adopt a sparse supervised loss and the proposed unsupervised loss. In addition, we adopt a loss for modeling the uncertainty of the pseudo ground-truth produced by the weak branch and a feature consistency loss. $\| \cdot \|_1$ and $\| \cdot \|_2$ are $\ell_1$ and $\ell_2$ loss functions, respectively.

**Sparse Supervised Loss.** When sparse depth-labeled data is available to train the network, we can minimize the supervised loss function $L_{\text{gt}}$ between predicted $D$ and sparse ground-truth $D_{\text{gt}}$ such that

$$L_{\text{gt}} = \| D - D_{\text{gt}} \|_1.$$  \hspace{1cm} (3)

In our framework, a small number of fully annotated data used in a supervised manner allows the depth estimation model to ignite the learning process, which is then carried out mainly on unlabeled data through consistency regularization.

**Depth Consistency Loss.** We formulate a loss that encourages depth prediction of the strongly-augmented image to be close to the prediction of the weakly-augmented image. Since this loss function does not require annotated ground-truths and enables pixel-level learning, it serves as an effective solution to data hunger caused by sparse annotations. The depth consistency loss $L_{\text{dc}}$ assisted by the uncertainty map $U(D_{\text{weak}})$ can be written as:

$$L_{\text{dc}} = \text{stopgrad}(U(D_{\text{weak}}))\cdot\|\text{stopgrad}(D_{\text{weak}}) - D_{\text{strong}}\|_1.$$  \hspace{1cm} (4)

**Uncertainty Loss.** Ignoring the regions with high uncertainty allows for transferring only the reliable depth knowledge from weak branch to strongly augmented branch. To model such uncertainty, we leverage a negative log-likelihood minimization [35] as

$$L_{\text{uc}} = \frac{\|D - D_{\text{gt}}\|_1}{U(D)} + \log(U(D)),$$  \hspace{1cm} (5)

where $U(D)$ denotes the uncertainty map related to the predicted depth map $D$. By training the network to model its uncertainty, predictions on unlabeled data will be trusted if highly confident, as shown in Fig 4.

**Feature Consistency Loss.** Within our framework, geometric distortions are not applied to the two branches, and thus the encoded feature consistency can also be encouraged. The feature consistency loss is then defined as

$$L_{\text{fc}} = \|z_{\text{weak}} - h(z_{\text{strong}})\|_2.$$  \hspace{1cm} (6)

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Figure 5. **Quantitative results on the KITTI dataset in a sparsely-supervised setting.** ‘Baseline’ only uses a sparse depth, and ‘Self’ indicates existing self-supervised strategies [24,29]. ‘Ours’ indicates the proposed semi-supervised learning framework.
where $h(\cdot)$ is an additional MLP predictor head, which provides better results as shown in the literature [12, 30] and prevents collapse [79].

**Total Loss.** By considering all the terms introduced so far, the final loss is defined as

$$\mathcal{L} = \mathcal{L}_{gt} + \lambda_{uc}\mathcal{L}_{uc} + \lambda_{dc}\mathcal{L}_{dc} + \lambda_{fc}\mathcal{L}_{fc},$$

(7)

where $\lambda_{uc}$, $\lambda_{dc}$, and $\lambda_{fc}$ represent weighting parameters.

### 4. Experiments

#### 4.1. Implementation Details

We implemented our networks with the Pytorch library [51]. We conduct all our experiments with 24GB RTX-3090 GPUs, using DPT [56] as a backbone model. We set the learning rate to $10^{-5}$ for the encoder and $10^{-4}$ for the decoder. The encoder is initialized with ImageNet-pretrained [16] weights, whereas the decoder is initialized randomly. We train the entire model with batch size 8 and use Adam optimizer with $\beta_1 = 0.9$ and $\beta_2 = 0.999$.

To avoid collapsing, we balance the ratio of labeled and unlabeled data in one batch to 1:7 similarly to [60]. Besides our new data augmentation approach, we adopt flipping and jittering, widely used in the literature [20, 26]. For confidence estimation, we train the network to predict the log variance because it is more numerically stable [35] than regressing the variance itself, as the loss avoids any division by zero. We use an identical hyperparameter set (i.e., $\lambda_{uc} = 1$, $\lambda_{dc} = 1$, $\lambda_{fc} = 1$, $K = 64$ for strong augmentation) for all experiments unless otherwise specified.

#### 4.2. Experimental Settings

**Dataset.** We first evaluate the performance of our model and others on the KITTI dataset [25] and NYU-Depth-v2 [59]. KITTI dataset [25] provides outdoor scenes captured by 3D laser data. The RGB images are resized to $640 \times 192$ resolutions for training. We follow the standard Eigen training/testing split [21]. We use randomly sampled 10,000, 1,000, and 100 images from $24K$ (i.e., left frames in the Eigen training split) for labeled images during training. We evaluate our trained model on 652 annotated test images for single-view depth estimation, using the improved ground-truth by [65]. NYU-Depth-v2 dataset [59] is composed of various indoor scenes and corresponding depth maps at a resolution of $640 \times 480$. We train our network on the same number of labeled images as KITTI, randomly sampled from the original $40K$ training images. The remaining images in the training set are used as unlabeled images. We test our trained model on 654 test images.

**Evaluation Metrics.** In our experiments, we follow the standard evaluation protocol of the prior work [21] to evaluate the effectiveness of our framework. The error metrics are defined as Absolute Relative error (AbsRel), Squared Relative error (SqRel), Root Mean Squared Error (RMSE), Root Mean Squared log Error (RMSElog), and accuracy under the threshold ($< 1.25$) ($\delta$).

#### 4.3. Depth Estimation Results

In this section, we investigate the effects of sparse labels on supervised depth training, and how our proposed semi-supervised learning framework is able to mitigate degra-
Table 1. **Quantitative results** comparing our method against the existing approaches on the Eigen split of the KITTI dataset, using improved ground truth. 'Sup.', 'Self.(M)', and 'Self.(S)' indicate supervised, existing self-supervised strategies on video and stereo pairs, respectively. 'Self.' denotes our proposed consistency regularization, which needs no stereo images or video sequences. 'K', 'C', and 'F' indicate KITTI, Cityscapes, and FlyingThings3D, respectively. 'Mix' indicates the dataset proposed from [56], which is approximately 60 times larger than KITTI, which contains 1.4M images (DB.). '*' denotes run by ourselves.

| Methods | Sup. | Self.(M) | Self.(S) | DB. | AbsRel↓ | SqRel↓ | RMSE↓ | RMSElog↓ | δ↑ |
|---------|------|----------|----------|-----|---------|--------|--------|-----------|-----|
| DORN    | ✓    | -        | -        | K   | 0.072   | 0.307  | 2.727  | 0.120     | 0.932|
| BTS     | ✓    | -        | -        | K   | 0.059   | 0.241  | 2.756  | 0.096     | 0.959|
| DPT-Hybrid | ✓    | -        | -        | K   | 0.062   | 0.254  | 2.573  | 0.092     | 0.959|
| DPT-Base* | ✓    | -        | -        | K   | 0.074   | 0.361  | 3.275  | 0.117     | 0.935|
| Monodepth2 | -    | ✓        | ✓        | K   | 0.080   | 0.466  | 3.681  | 0.127     | 0.926|
| PackNet-SIM | -    | ✓        | -        | K   | 0.078   | 0.420  | 3.485  | 0.121     | 0.931|
| ManyDepth | -    | ✓        | -        | K   | 0.070   | 0.399  | 3.455  | 0.113     | 0.941|
| SVSM FT | ✓    | -        | ✓        | K+F | 0.077   | 0.392  | 3.569  | 0.127     | 0.919|
| Kuznietsov et al. | ✓    | -        | ✓        | K   | 0.089   | 0.478  | 3.610  | 0.138     | 0.906|
| Baek et al. | ✓    | ✓        | ✓        | K   | 0.078   | 0.381  | 3.404  | 0.121     | 0.930|
| Guizilini et al. | ✓    | ✓        | -        | K   | 0.072   | 0.340  | 3.265  | 0.116     | 0.934|
| SemiDepth | ✓    | -        | ✓        | K   | 0.078   | 0.417  | 3.464  | 0.126     | 0.923|
| Ours (DPT-Base) | ✓    | -        | -        | K+C | 0.071   | 0.316  | 3.049  | 0.111     | 0.941|

Table 2. **Quantitative results** comparing our method against the existing approaches on the NYU-Depth-v2 dataset. 'N' and 'S' indicate NYU-Depth-v2 and SUN RGB-D datasets, respectively.

We trained our model on the KITTI dataset [25] as labeled, and the additional Cityscape dataset [15] as unlabeled data. In the results, our method achieves significant improvement in comparison to the baseline by utilizing unlabeled data and surpasses the state-of-the-art in semi-supervised depth estimation methods. Moreover, our method shows competitive performance against DPT-Hybrid, despite smaller model capacity and fewer annotated data being used. A similar trend can be seen in Table 2, where our method utilizes SUN RGB-D [61] dataset as an additional unlabeled dataset and NYU-Depth-v2 as labeled data.

### 4.4. Ablation Study

For our ablation study, we analyze the effectiveness of different design choices in our framework on KITTI [25]. We exploit 10,000 and 100 randomly sampled images for data augmentation and other ablation studies, respectively.

**Data Augmentation.** We evaluate our proposed K-way disjoint masking as augmentation in comparison to different MIM methods, including SimMIM [74] and MAE [32], and another data augmentation method, CutOut [18] in either fully supervised or semi-supervised settings with a base-
### Table 3. Impact of data augmentation.

| Method        | AbsRel ↓ | RMSE ↓ | δ↑ | AbsRel ↓ | RMSE ↓ | δ↑ |
|---------------|----------|--------|----|----------|--------|----|
| Baseline      | 0.078    | 3.370  | 0.930 | -         | -      | -  |
| CutOut        | 0.076    | 3.302  | 0.932 | 0.075     | 3.351  | 0.931 |
| SimMiM        | 0.077    | 3.338  | 0.931 | 0.076     | 3.363  | 0.931 |
| MAE           | 0.075    | 3.291  | 0.933 | 0.074     | 3.280  | 0.934 |
| Ours          | 0.076    | 3.289  | 0.934 | 0.075     | 3.239  | 0.937 |

Table 4. Ablation study on main components: Depth consistency (D), Uncertainty (U), and Feature consistency (F).

Loss Functions. We examine each component of the loss function of our method. It consists of four components: sparse supervised term, depth consistency term, feature consistency term, and uncertainty term. Starting with using only sparse supervised loss as the baseline, we study the other three components. As shown in Table 4, the performance of our network improves as each component of the loss function is added. We can see that using all components together leads to a significant improvement.

Predictor Head. To improve the representation power of the encoder, we consider feature consistency loss between encoded features. When the predictor head was removed, collapsing occurred and training did not reach convergence. Our framework without predictor head is conceptually analogous to a naive siamese network, which could not avoid collapsing [79].

The number of $K$. To study the influence of the masking ratio, we train the network by adopting different values of $K$ for the strong branch, respectively $K = 4, 16, 64,$ and $128$. Table 6 shows the quantitative evaluation results for this study. Starting from $K = 4$, the error decreases with the increase of $K$, until degrading for $K = 128$. We set $K = 64$ as the default since it yields the best results.

4.5. Domain Adaptation

Inspired by [48], we simply apply our framework to unsupervised domain adaptation methods using virtual KITTI (vKITTI) [23] and KITTI [25] as synthetic and real datasets respectively. As demonstrated in Table 7, our framework is lightweight and easily adaptable, yet still achieves reasonable performance compared to generative models.

5. Conclusion

In this paper, we introduced a novel semi-supervised framework for monocular depth estimation using consistency regularization. To this end, we proposed a data augmentation method, called $K$-way disjoint masking, allowing for leveraging unlabeled data without requiring either stereo or sequential frames. Moreover, the proposed method showed improvement on extremely sparse ground-truth data and superior results compared to other semi-supervised approaches. For future work, we plan to expand our method to other dense prediction tasks.

Acknowledgements. This research was supported in part by Autonomous Driving Center, R&D Division, Hyundai Motor Company.
Appendix

In this appendix, we provide more results on experiments carried out and more implementation details of our framework.

Appendix A. More Quantitative Results

More detailed quantitative results of our proposed method and conventional self-supervised method on KITTI dataset [25] are shown in Table 8. Moreover, to verify generalization ability of our framework, we evaluated our framework on NYU-Depth-v2 dataset [59]. Results are shown in Table 9.

| Methods       | # sup. frames | AbsRel ↓ | SqRel ↓ | RMSE ↓ | RMSElog ↓ | δ↑  |
|---------------|---------------|----------|---------|--------|------------|-----|
| Baseline      | 23,158        | 0.076 ± 0.003 | 0.365 ± 0.004 | 3.290 ± 0.015 | 0.118 ± 0.001 | 0.934 ± 0.001 |
|               | 10,000        | 0.079 ± 0.001 | 0.379 ± 0.007 | 3.388 ± 0.019 | 0.121 ± 0.009 | 0.929 ± 0.001 |
|               | 1,000         | 0.098 ± 0.004 | 0.515 ± 0.030 | 3.785 ± 0.013 | 0.142 ± 0.005 | 0.899 ± 0.005 |
|               | 100           | 0.135 ± 0.005 | 0.728 ± 0.019 | 4.585 ± 0.048 | 0.186 ± 0.011 | 0.831 ± 0.005 |
|               | 10            | 0.201 ± 0.023 | 1.508 ± 0.045 | 6.163 ± 0.082 | 0.268 ± 0.029 | 0.701 ± 0.021 |
| Baseline + Self.(M) | 23,158       | 0.076 ± 0.002 | 0.367 ± 0.007 | 3.291 ± 0.020 | 0.117 ± 0.001 | 0.933 ± 0.002 |
|               | 10,000        | 0.078 ± 0.001 | 0.376 ± 0.006 | 3.347 ± 0.043 | 0.119 ± 0.002 | 0.931 ± 0.001 |
|               | 1,000         | 0.096 ± 0.002 | 0.523 ± 0.024 | 3.750 ± 0.033 | 0.140 ± 0.002 | 0.900 ± 0.004 |
|               | 100           | 0.132 ± 0.004 | 0.759 ± 0.014 | 4.559 ± 0.044 | 0.184 ± 0.003 | 0.834 ± 0.004 |
|               | 10            | 0.210 ± 0.020 | 1.322 ± 0.042 | 5.627 ± 0.080 | 0.265 ± 0.027 | 0.711 ± 0.016 |
| Ours+Self.(M) | 23,158        | 0.079 ± 0.001 | 0.379 ± 0.007 | 3.388 ± 0.019 | 0.121 ± 0.009 | 0.929 ± 0.001 |
|               | 10,000        | 0.076 ± 0.017 | 0.369 ± 0.004 | 3.311 ± 0.011 | 0.117 ± 0.001 | 0.935 ± 0.002 |
|               | 100           | 0.123 ± 0.003 | 0.747 ± 0.018 | 4.497 ± 0.042 | 0.181 ± 0.005 | 0.839 ± 0.005 |
|               | 10            | 0.184 ± 0.011 | 1.265 ± 0.064 | 5.747 ± 0.080 | 0.243 ± 0.007 | 0.727 ± 0.018 |
| Ours          | 23,158        | 0.074 ± 0.001 | 0.362 ± 0.001 | 3.253 ± 0.012 | 0.116 ± 0.001 | 0.935 ± 0.001 |
|               | 10,000        | 0.075 ± 0.002 | 0.362 ± 0.006 | 3.259 ± 0.020 | 0.116 ± 0.001 | 0.934 ± 0.003 |
|               | 1,000         | 0.088 ± 0.003 | 0.419 ± 0.007 | 3.490 ± 0.020 | 0.129 ± 0.003 | 0.917 ± 0.002 |
|               | 100           | 0.128 ± 0.004 | 0.707 ± 0.013 | 4.295 ± 0.037 | 0.173 ± 0.006 | 0.849 ± 0.006 |
|               | 10            | 0.197 ± 0.019 | 1.378 ± 0.032 | 5.650 ± 0.091 | 0.261 ± 0.030 | 0.723 ± 0.017 |

Table 8. Quantitative results on the KITTI dataset [25] in a sparsely-supervised setting using sparse labels from [65]. For each row, we trained 5 independent models with randomly selected labels from entire dataset to calculate the mean and variance. ‘Self.(M)’ and ‘Ours’ indicate monocular self-supervised learning and proposed consistency regularization, respectively. The best results are in **bold**.
### Table 9. Quantitative results on the NYU-Depth-v2 dataset [59] in a sparsely-supervised setting. For each row, we trained 5 independent models with randomly selected labels from entire dataset to calculate the mean and variance.

#### Methods

| Methods | # sup. frames | AbsRel ↓ | RMSE ↓ | log10 ↓ | δ↑ |
|---------|---------------|----------|--------|---------|----|
| Baseline | 42,602 | 0.106 ± 0.002 | 0.380 ± 0.004 | **0.053 ± 0.001** | 0.897 ± 0.001 |
| | 10,000 | 0.112 ± 0.004 | 0.389 ± 0.006 | 0.057 ± 0.003 | 0.893 ± 0.003 |
| | 1,000 | 0.141 ± 0.008 | 0.447 ± 0.009 | 0.066 ± 0.004 | 0.843 ± 0.006 |
| | 100 | 0.199 ± 0.011 | 0.604 ± 0.014 | 0.086 ± 0.005 | 0.694 ± 0.011 |
| | 10 | 0.321 ± 0.040 | 0.872 ± 0.042 | 0.124 ± 0.008 | 0.523 ± 0.027 |
| Ours | 42,602 | **0.105 ± 0.002** | **0.379 ± 0.003** | **0.053 ± 0.001** | **0.899 ± 0.001** |
| | 10,000 | **0.107 ± 0.002** | **0.386 ± 0.006** | **0.054 ± 0.002** | **0.896 ± 0.002** |
| | 1,000 | **0.135 ± 0.007** | **0.440 ± 0.008** | **0.065 ± 0.004** | **0.853 ± 0.005** |
| | 100 | **0.182 ± 0.008** | **0.594 ± 0.012** | **0.083 ± 0.003** | **0.718 ± 0.010** |
| | 10 | **0.292 ± 0.031** | **0.814 ± 0.037** | **0.112 ± 0.006** | **0.561 ± 0.021** |

#### Appendix B. More Qualitative Results

In the main paper, we have visualized the comparisons of baseline and our methods on NYU-Depth-v2 dataset [59] and KITTI dataset [25]. In this section we provide additional qualitative results after having trained on 100 and 10,000 frames in Fig 8 and Fig 9. Our method shows better results, especially at semantic level and object boundaries, while the baseline approach shows poor result on them.

![Figure 8. Qualitative results on the NYU-Depth-v2 dataset [59]: (a) RGB image, (b) ground-truth depth map, and predicted depth maps by (c), (e) baseline, and (d), (f) ours using 100 and 10,000 labeled frames, respectively.](image-url)
Figure 9. **Qualitative results on the KITTI dataset [25]**: (a) RGB image, (b) ground-truth depth map, and predicted depth maps by (c), (e) baseline, and (d), (f) ours using 100 and 10,000 labeled frames, respectively.
Appendix C. More Implementation Details

PyTorch-like Pseudo-code for $K$-way disjoint masking modeling. We provide pseudo-code for $K$-way disjoint masking modeling, in order to show how our novel technique can be implemented independently. This enables the effect of data augmentation while preserving the geometry.

Algorithm 1: Pseudo Code of $K$-way disjoint masking modeling

```python
# Input: Transformer are basic transformer encoder blocks
# Input: X (B x N x P) is patch embeddings
# where N is number of patches and P is embedding dimension
# Input: K is number of masking subsets.
# Output: Z (B x N x P) is K-way disjointly encoded features
def K_way_masked_transformer(transformer, X, K):
    B, N, _ = X.shape
    batch_range = torch.arange(B)[..., None]
    rand_indices = torch.rand(B, N).argsort(dim = -1)
    X = X[batch_range, rand_indices]
    # patch wise random shuffling on X
    # X is no longer spatial order after shuffling
    v = sorted([random.randint(1,N-1) for i in range(int(K-1))] + [0, N])
    # sampling subset split point randomly
    mask_v = torch.zeros(len(v[:-1]), N)
    for i in range(len(v[:-1])):
        mask_v[i, v[i]:v[i+1]] = 1.0
    # mask has shape of (B x N x N)
    # attention matrix masking from different subset
    # by applying this attention mechanism proceeds semi-globally
    Z_ = transformer(x, attention_mask)
    # Z (B x N x P)) is K-way masked token embeddings
    reform_indices = torch.argsort(rand_indices, dim=1)
    return Z_[batch_range, reform_indices]
    # reassemble features to spatial order and return

# In the transformer, attention method
# Input: Q, K, V (B x N x P) is Query, Key, Value vectors
# Input: mask (B x N x N) attention mask
# Output: V' (B x N x P) mask attentioned Value vectors
def attention(Q, K, V, mask):
    dots = torch.matmul(Q, K.transpose(-1, -2)) * sqrt(Q.shape[-1])
    # general attention matrix that has shape of (B x N x N)
    if not(mask == None):
        dots[:,:, mask==0.0] = -10.0
        # replace value of masked region with negatives befor softmax
        # so it’s attention distribution value goes nearly zero after softmax
    attn = Softmax(dots, dim=-1)
    V = torch.matmul(attn, V)
    return V
```

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| Layer          | Parameters (in, out, k, s, p) | Output shape (C × H × W) |
|---------------|-------------------------------|--------------------------|
| Conv          | (3, 768, 16, 16, 0)          | (768, 12, 40)            |
| Rerange       |                               | (HW = 480, C = 768)      |

### Transformer Encoder \# blocks

| Layer          | Parameters (in, out) | Output shape (C) |
|---------------|---------------------|-----------------|
| LayerNorm     | -                   | (768)           |
| Linear-N-1    | (768, 2304)         | (2304)          |
| Attention     | -                   | (768)           |
| Linear-N-2    | (768, 768)          | (768)           |
| LayerNorm     | -                   | (768)           |
| Linear-N-3    | (768, 3072)         | (3072)          |
| GELU          | -                   | (3072)          |
| Linear-N-4    | (3072, 768)         | (768)           |

| Layer          | Parameters (in, out, k, s, p) | Output shape (C × H × W) |
|---------------|-------------------------------|--------------------------|
| Conv-1(Linear-2-4) | (768,96,1,1,0)                           | (96,12,40)              |
| ConvTranspose-1 | (96,96,4,4,0)                             | (96,48,160)             |
| Conv-2         | (96,256,3,1,1)                             | (256,48,160)            |
| Conv-3(Linear-5-4) | (768,192,1,1,0)                           | (192,12,40)             |
| ConvTranspose-2 | (192,192,2,2,0)                            | (192,24,80)             |
| Conv-4         | (192,256,3,1,1)                            | (256,24,80)             |
| Conv-5(Linear-8-4) | (768,384,1,1,0)                           | (384,12,40)             |
| Conv-6         | (384,256,3,1,1)                            | (256,12,40)             |
| Conv-7(Linear-11-4) | (768,768,1,1,0)                           | (768,12,40)             |
| Conv-8         | (768,768,3,2,1)                            | (768,6,20)              |
| Conv-9         | (768,256,3,1,1)                            | (256,6,20)              |

### Decoder

| Layer          | Parameters (in, out, k, s, p) | Output shape (C × H × W) |
|---------------|-------------------------------|--------------------------|
| ReLU          | -                             | (256,h,w)                |
| Conv-10       | (256,256,3,1,1)               | (256,h,w)                |
| RELU          | -                             | (256,h,w)                |
| Conv-11       | (256,256,3,1,1)               | (256,h,w)                |
| RELU          | -                             | (256,h,w)                |
| Fusion-1(Conv-9) | -                           | (256,6,20)               |
| UpSample      | -                             | (256,12,40)              |
| Conv-12       | (256,256,1,1,1)               | (256,12,40)              |
| Fusion-2(Conv-6) | -                           | (256,12,40)              |
| add-2(Fusion-2,Conv-12) | -                      | (256,12,40)              |
| Fusion-4(add-2) | -                           | (256,12,40)              |
| UpSample      | -                             | (256,24,80)              |
| Conv-13       | (256,256,1,1,1)               | (256,24,80)              |
| Fusion-5(Conv-4) | -                           | (256,24,80)              |
| add-3(Fusion-5,Conv-13) | -                    | (256,24,80)              |
| Fusion-6(add-3) | -                           | (256,24,80)              |
| UpSample      | -                             | (256,24,80)              |
| Conv-14       | (256,256,1,1,1)               | (256,24,80)              |
| Fusion-7(Conv-2) | -                           | (256,48,160)             |
| add-4(Fusion-7,Conv-14) | -                      | (256,48,160)             |
| Fusion(add-4)  | -                             | (256,48,160)             |
| UpSample      | -                             | (256,48,160)             |
| Conv-15       | (256,256,1,1,1)               | (256,48,160)             |
| Conv-16       | (256,128,3,1,1)               | (128,96,320)             |
| UpSample      | -                             | (256,128,3,1,1)          |
| Conv-17       | (128,32,3,1,1)                | (32,96,320)              |
| ReLU          | -                             | (32,96,320)              |
| Conv-18       | (32,1,1,1,0)                  | (1,192,640)              |
| sigmoid       | -                             | (1,192,640)              |

### Fusion(x)

| Layer          | Parameters (in, out, k, s, p) | Output shape (C × H × W) |
|---------------|-------------------------------|--------------------------|
| Table 10. Network architecture of our model. | 13 |
Network Architecture Details. We summarize the detailed network architecture of our model in Table 10. Our encoder basically follows ViT [19] without class token. We use 12 transformer blocks (ViT-Base) and extract features 2, 5, 8, and 11 for skip connection input \((0 \leq N \leq 11)\). The Decoder structure follows DPT [56], and the Decoder part in the Table 10 indicates 4 skip connections. However, there are no readout operations, because no class token is used.

Appendix D. Qualitative Results of Domain Adaptation

In our main paper, we demonstrated that our framework is lightweight, easy to use for domain adaptation, and has reasonable performance compared to other techniques. We also show the qualitative results of our domain adaptation experiments in Fig 10.

Figure 10. Qualitative results on the KITTI dataset [25]: (a), (c) RGB image, and (b), (d) depth map. Our framework proves to work well in domain adaptation task on real-world images.

Appendix E. Limitations and Broader Impact

Limitations. In this paper, we introduce a novel framework semi-supervised depth estimation method using consistency regularization. However, our approach learns unlabeled data by following the guidance of a small number of labeled data, so it may fail to predict depth in sparse annotations such as sky regions. Another limitation is that our method performs well on the KITTI dataset [25], while the performance improves relatively less on images with a higher variety of content, e.g., as in the NYU-Depth-v2 dataset [59].

Broader Impact. In the future, we aim to apply our method in various data domains, and develop the performance of our framework by leveraging the newly studied data augmentation techniques. Our work is an essential study in order to be completely free from the dependence of the data, and provides the possibility to replace the existing self-supervised methods requiring additional images.
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