Learning Depth via Leveraging Semantics: Self-supervised Monocular Depth Estimation with Both Implicit and Explicit Semantic Guidance

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Abstract

Self-supervised depth estimation has made a great success in learning depth from unlabeled image sequences. While the mappings between image and pixel-wise depth are well-studied in current methods, the correlation between image, depth and scene semantics, however, is less considered. This hinders the network to better understand the real geometry of the scene, since the contextual clues, contribute not only the latent representations of scene depth, but also the straight constraints for depth map. In this paper, we leverage the two benefits by proposing the implicit and explicit semantic guidance for accurate self-supervised depth estimation. We propose a Semantic-aware Spatial Feature Alignment (SSFA) scheme to effectively align implicit semantic features with depth features for scene-aware depth estimation. We also propose a semantic-guided ranking loss to explicitly constrain the estimated depth maps to be consistent with real scene contextual properties. Both semantic label noise and prediction uncertainty is considered to yield reliable depth supervisions. Extensive experimental results show that our method produces high quality depth maps which are consistently superior either on complex scenes or diverse semantic categories, and outperforms the state-of-the-art methods by a significant margin.

1. Introduction

Depth estimation is a long-standing problem in computer vision, which is widely used in robotic perception, autonomous driving as well as multimedia applications [36, 13], etc. Compared with classical geometry-based methods [33, 24] which estimate depth using stereo or sequential images, learning-based methods [12, 11, 23] are able to conduct pixel-wise dense predictions given only a single image as input. However, as the deep neural network requires a large amount of labeled data for training, ideal depth labels are hard to acquire due to the expensive Li-

Figure 1: Example of monocular depth estimation. Compared with the SOTA method [18], our method successfully recognizes the object depth from unusual categories (left blue box). At the mean time, our method generates high quality depth map which possesses smooth depth change inside the object region (right green box) and sharp depth edge across object borders (right red box).
umn of Figure 1, SOTA method [18] failed to infer the depth of a truck with unusual vehicle properties than other cars. On the other hand, image semantics also provide straight clues for object depth. Typically, the semantic borders also correspond to depth borders, and the depth distribution of each individual object is category-specific. For example, objects such as “person” and “traffic sign” possess uniform depth in the scene, while categories “buildings” and “road” exhibit gradual depth change. This raises new challenges for conventional methods. As shown in the right column, [18] produces obvious “bleeding artifacts” [48] in the depth borders, and the abnormal sudden depth changes are also observed inside an continuous object area.

In order to fully exploit the benefits of image semantics for depth estimation, we propose to impose semantic guidances in implicit and explicit ways, respectively. In our framework, we extract semantic features by a semantic segmentation branch, and fuse them with a depth estimation branch at feature level to assist model prediction. In this way, image semantics are combined with image representation to implicitly guide depth estimation. Based on the analysis that the depth distribution is highly related to the semantic categories, we further propose the Semantic-aware Spatial Feature Alignment (SSFA) module, which spatially aligns depth and semantic features via constraining depth distribution to be consistent inside the same category area, while to be different across other categories. During this process, semantic category information is used as external prior to guide the feature alignment. We further propose the semantic-guided ranking loss to explicitly improve the estimated depth map quality. Given semantic labels, we sample a set of cross-edge point quadruplets to explicitly constrain the depth map to be smooth inside the semantic object areas, while to have sharp depth edges across the semantic borders. Different from other edge-based methods [48, 4], we take the impact of erroneous semantic labels into consideration, and propose robust point pair sampling strategy and semantically uncertainty-aware weighting to alleviate semantic label noise. As shown in Figure 1, the proposed implicit and explicit semantic guidances yield accurate depth estimation under different challenging scenarios.

Our contribution can be concluded as follows:

- We address the advantages of leveraging image semantics for both image depth inference and depth map fine-tuning. We thus propose implicit and explicit semantic guidances to fulfill the two objectives respectively.

- We propose a novel Semantic-aware Spatial Feature Alignment (SSFA) scheme to effectively guide depth estimation in an implicit manner, and propose the semantic-guided ranking loss to explicitly improve the accuracy of estimated depth map.

- Our method generates consistently superior results across different scenarios and semantic categories, quantitative results on KITTI show that it outperforms the state-of-the-art self-supervised monocular trained methods by a significant margin.

2. Related Work

**Self-supervised depth estimation.** Self-supervised methods cast the depth supervision problem into image-based supervision, which enables learning without depth annotations. As the pioneer methods [16, 14] train depth networks using stereo image pairs, Zhou et al. [47] propose a more generalized pipeline, which enables training with pure image sequences. After that, great progress has been made to improve self-supervised framework in terms of loss, occlusion removal as well as architectures. Yang et al. [44] and Li et al. [25] enhance the photometric loss to be robust towards illumination variance, while Shu et al. [34] propose the feature-metric loss which improves the loss back propagation on low gradient areas. In order to solve the scene occlusion as well as object motion issues during depth training, several methods [47, 17, 2, 38] propose both learning-based and geometric selective mask that filter out the unreliable losses. In order to exploit more information for self-surpervised methods, optical flow is introduced [32, 41, 45] for extra constraints. Pseudo depth is also leveraged as extra prior information [46]. In terms of new self-supervised architectures, Guizilini et al. [18] propose novel packing and unpacking modules which preserves more detailed depth predictions. However, in this paper, for fair comparison, we rule out the influence of new network architectures when comparing with the state-of-the-arts.

**Semantic guidance for depth estimation.** Semantic segmentation has shown its effectiveness for depth estimation in previous works [7, 19, 4, 31]. The methods can be categorized into two groups according to how image semantics are used. The first group of methods offer implicit semantic guidance via providing feature-level information. Chen et al. [4] generate both depth and semantic maps with a unified scene representation. Guizilini et al. [19] propose to feed the PAC enhanced [35] pre-trained segmentation features for depth estimation. Choi et al. [7] leverage the semantic network and feed the features with cross-propagation and affine-propagation unit. Though we also fuse image depth with semantics in feature level, we align semantic features in a more solid way through our proposed SSFA module, which provides image semantic guidance with distinctly more fidelity and persistence.

The other group of methods use semantic categories to explicitly constrain or supervise depth networks. Ramirez et al. [31] and Chen et al. [4] constrain the smoothness of the depth map using semantic maps. Casser et al. [3] and Klingner et al. [22] handle the dynamic moving object is-
3. The Proposed Method

Self-supervised depth estimation usually takes image triplet \((I_{t-1}, I_t, I_{t+1})\) as input, where \(I_t\) is the target image and \(I_{t'} \in \{I_{t-1}, I_{t+1}\}\) belongs to the source images. During training, \(I_t\) is fed into the depth network \(f_D\) to get the predicted depth \(\hat{D}_t \in \mathbb{R}^{H \times W}\), where \(H\) and \(W\) are the image height and width. \((I_t, I_{t'})\) are put into the motion network to get the relative motion \(T_{t' \rightarrow t}\). Then, the synthesized image \(I_{t' \rightarrow t}\) can be computed with \(I_t, \hat{D}_t\) and \(T_{t' \rightarrow t}\) \cite{godard2019digging}. The depth network is trained by back-propagating the photometric loss between the synthesized images \(I_{t' \rightarrow t}\) and the target image \(I_t\), as proposed by Godard et al. \cite{godard2019digging}.

\[
L_{ph}(I_t, I_{t' \rightarrow t}) = \min_{t'} \left(\frac{\alpha}{2} (1 - \text{SSIM}(I_t, I_{t' \rightarrow t})) + (1 - \alpha) \|I_t - I_{t' \rightarrow t}\|_1\),
\]

where SSIM denotes the structural similarity index \cite{wang2004image}, \(\alpha\) refers to the weighting factor which is commonly set to 0.85 \cite{godard2019digging, wang2019mask2depth, godard2019digging}. The first-order depth smoothness loss \(L_s\) is also set with the weighting factor of \(10^{-3}\) \cite{wang2019mask2depth}.

In this paper, we follow the basic self-supervised framework but extend it with implicit and explicit semantic guidance for accurate depth estimation. During depth inferring, we introduce a SSFA module to incorporate image semantics, which implicitly makes the estimated depth semantically aware. We further explicitly constrain the estimated depth map with semantic-guided ranking loss, and improve the accuracy and reliability of our predicted depth map. The overview of our model is shown in Figure 2.

3.1. Semantic-aware Feature Alignment Scheme

We enhance the depth estimation performance implicitly by providing semantic feature representations to the depth network. Thus, a semantic branch is proposed to offer semantic category-level information in a multi-scale scheme, see Section 3.1.1. Consider the semantic and depth features are from the different task domains, we align the features by the proposed semantic-aware spatial feature alignment (SSFA) module, utilizes external semantic category-level labels for better semantic guidance, see Section 3.1.2.

3.1.1 Semantic Multi-task Scheme

We extend the general self-supervised depth estimation framework by add an extra semantic branch \(f_S\), which shares the same encoder with the depth network, as shown in the top of Figure 3. Given the input image \(I\), a semantic probability map \(\hat{S}_b \in [0, 1]^{H \times W}\) is generated and super-

![Figure 2: The overview of the proposed architecture.](image)
vised by the given binary semantic label $S^b \in \{0, 1\}^{H \times W}$

$$L_M = \text{BCELoss}(\hat{S}^b, S^b),$$ (2)

where $\text{BCELoss}(\cdot)$ denotes the binary cross-entropy loss. The semantic labels can be either groundtruth or pre-computed labels from other methods; we use the latter [49] in our experiments due to the lack of semantic groundtruth annotations. Let $S \in M^{H \times W}$ be the full semantic label, where $M$ is the integers denoting the semantic categories. We generate the binary semantic label $S^b$ by specifying foreground objects of the given $S$. The reasons for generating the binary semantic map are twofold, 1) it provides comparable informative semantic features to the depth branch as the full semantic map does [1], 2) when using pre-computed semantic labels, cross-domain trained segmentation method [49] achieves much higher mIoU for binary predictions than full category predictions, which indicates that binary labels are more reliable as the input. Experimental details can be found on Section 4.6. The semantic branch is trained together with the depth network, and provides latent semantic features to the depth decoding layers in a multi-scale manner, as shown in Figure 3.

### 3.1.2 Semantic-aware Spatial Feature Alignment

Since the semantic and depth features are from different task domains, the simple fusions (direct concatenation or convolution, etc.) do not fully exploit the potential of image semantics for depth estimation. In this paper, consider the depth distribution of the scene is category-specific, we deduce the distribution of depth features should also be category-specific. Thus, we propose the Semantic-aware Spatial Feature Alignment (SSFA) module, which takes the semantic labels as external prior, to align the features and make them conform to the category-specific distributions, via semantic-aware spatial normalization operations.

As shown in Figure 3, during network training, we have multi-scale semantic features $F^i_S \in \mathbb{R}^{C_i \times H \times W}$ and depth features $F^i_D \in \mathbb{R}^{C_i \times H \times W}$, where $C_i$ denotes the channels of the feature block and $i \in \{0, 1, 2, 3, 4\}$. We propose 5 SSFA modules corresponding to the number of scales. For each input pair $(F^i_S, F^i_D)$, the corresponding SSFA module outputs the aligned feature $\hat{F}^i_D$ as the input of the next scale.

For each SSFA module, we propose two semantic-aware spatial alignment blocks (SAB) with residual connection as shown in the bottom of Figure 3. The SSFA module first fuses the two features together and then put the coarsely fused feature $F^i_{S+D}$ into the two blocks. Given an input feature $F$ to the spatial alignment block, the block first normalizes the input feature in the channel-wise manner, then spatially align the normalized feature $F_{\text{norm}}$ with the learned category-specific multiplicative factor $\alpha$ and additive factor $\beta$, as inspired by [30, 40]

$$F_{\text{aligned}} = \alpha \odot F_{\text{norm}} \oplus \beta,$$ (3)

where $\odot$ and $\oplus$ denote element-wise multiplication and addition, $\alpha$ and $\beta$ are learned from the semantic labels via simple conventional layers. After the multi-level processing with the proposed SSFA modules, the output features $\hat{F}^i_D$ are endowed with better representation capabilities that both semantic and depth features are well aligned by the category-level semantic guidance.

### 3.2. Semantic-guided Ranking Loss

In this section, we explicitly constrain the generated depth map to be consistent inside semantic categories and to be sharp cross the category borders. We resort to the ranking loss [5] for it directly constrains the depth differences, which is more suitable to constrain depth sharpness/smoothness. Different from the existing depth ranking loss [5, 43] which use the point pair depth similarity to specify the maximize or minimize operation of depth difference, we instead propose a semantic-guided ranking loss, which maximize/minimize the point pair depth difference accord-
The proposed semantic-guided edge sampling strategy. For every edge point \(p_j^e\), we sample a point quadruplet \(Q = \{p_j^{S1}, p_j^{S2}, p_j^{N1}, p_j^{N2}\}\) along orthogonal line \(n\). To find the real border, we search the max gradient point \(p_j^g\) along \(n\) in range \([-r, r]\), and make the cross-border point pair \((p_j^{S1}, p_j^{N1})\) to clamp \(p_j^g\) and \(p_j^g\).

The strategy explicitly on the semantic borders, little noise on the semantic labels will cause erroneous constrains for the predicted depth. To address this problem, a cross-border point pair sampling strategy (see Section 3.2.1) and a semantically uncertainty-aware weighting factor (see Section 3.2.2) is proposed which consider the noise of input semantic labels.

### 3.2.1 Cross-border Point Pair Sampling Strategy

Inspired by [43], we propose to sample a set of point quadruplets \(Q = \{q_j\}_{j=1}^J\) on the semantic borders to compute the ranking loss, where \(J\) is the number of edge points. We first compute the edge map of the binary semantic label, and for every edge point \(p_j^e\), we sample a quadruplet \(q_j = \{p_j^{S1}, p_j^{S2}, p_j^{N1}, p_j^{N2}\}\) which contains 4 colinear points lying along the orthogonal line \(n\) crossing the edge point. As shown in Figure 4, point \(p_j^{S1}\) and \(p_j^{S2}\) lie on one side of \(p_j^e\), then point \(p_j^{N1}\) and \(p_j^{N2}\) lie on the other. Totally three point pairs \([p_j^{S1}, p_j^{S2}], [p_j^{S1}, p_j^{N1}], [p_j^{N1}, p_j^{N2}]\) are generated for computing the ranking loss.

While \([p_j^{S1}, p_j^{N1}]\) is supposed to be the cross-border point pair, the edge point \(p_j^e\) from noisy semantic labels are not reliable to represent the real object border. In this section, we solve this problem by incorporating image gradient as another clue to detect real object borders, for the object border points usually possess the largest gradient value in the local area. We search the maximum image gradient point \(p_j^g\) along the line \(n\), within a small distance range \(r\) to the edge point \(p_j^e\). As shown in Figure 4, when sampling the cross-border point, we set \([p_j^{S1}, p_j^{N1}]\) to clamp both \(p_j^g\) and \(p_j^g\) to make the sampled points across both semantic and image gradient border. The margin pixel \(\omega_1\) is set to 1 for tight clamping. The distance range \(r\) is set to \([-5, 5]\) empirically, in order to strike a balance between finding the real borders and making the sampled pairs close to the borders. For point \(p_j^{S2}\) and \(p_j^{N2}\), they are sampled besides the \(p_j^{S1}\) and \(p_j^{N1}\) respectively, within a distance range \(\omega_2\) which is set to \([2.5, 10]\). For each input image, we select all edge points and feed all corresponding quadruplets to compute the ranking loss in Equation 4. Besides the cross border point quadruplets set \(Q\), we also randomly sample a point pair set \(O = \{(p_k^a, p_k^b)\}_{k=1}^K\), whose point pairs lie inside the semantic borders, to constrain the depth smoothness in a broader range.

### 3.2.2 Semantically Uncertainty-aware Weighting

Although the cross-border sampling strategy in Section 3.2.1 heuristically constrains the point pairs to cross the real object border, it will fail when the pre-computed segmentation mask deviates significantly from the groundtruth. To address this problem, we propose a semantically uncertainty-aware weighting factor \(\gamma\) for Equation 4, which evaluate the quality of the input quadruplet \(q_j\) by leveraging semantic probabilities of the cross-border point pair. The semantic probability map \(\hat{S}_b\) is generated by the semantic branch \(f_s\). Though not being the ground truth probability, it indeed reflects the semantic uncertainties across different areas. Thus when computing the ranking loss of the three point pairs inside \(q_j\), the weighted loss \(L_{SR}^Q(p^a_j, p^b_j)\) is

\[
L_{SR}^Q(p^a_j, p^b_j) = \gamma \cdot L_{SR}(p^a_j, p^b_j),
\]

where \(p^a_j, p^b_j \in q_j\), the weighting value \(\gamma \in [\frac{1}{2}, 1]\) is decided by the differences of semantic probabilities between the point pair \(p_j^{S1}\) and \(p_j^{N1}\)

\[
\gamma = \exp(-1/\max(\hat{S}_b(p_j^{S1}), \hat{S}_b(p_j^{N1}))/\hat{S}_b(p_j^{S1}))) \cdot \hat{S}_b(p_j^{S1})/\hat{S}_b(p_j^{S1})).
\]

This means the more confident the semantic network is to its predicted cross-border points, the larger weight will be
assign to the three ranking losses. Note that for the points pairs $O, L_{SR}^O(p_{k1}, p_{k2}) = L_{SR}(p_{k1}, p_{k2})$. The final ranking loss $L_{SR}$ can be formulated as

$$L_{SR} = \frac{1}{3} \sum_j L_{SR}^Q(p_j, p_{k_j}^1) + \frac{1}{K} \sum_k L_{SR}^O(p_k, p_{k}^2)$$

(8)

### 3.3. Final Loss

The final loss of the whole pipeline can be formulated as

$$L = L_{ph} + L_M + \delta_s L_s + \delta_t L_{SR},$$

(9)

where $\delta_s$ is set to 0.001 for common practice [17], and $\delta_t$ is set to 0.001 empirically that it strikes a balance between overall performance and depth sharpness/smoothness.

### 4. Experiments

In this section, we conduct comprehensive comparisons to demonstrate the superiority of our method toward the state-of-the-arts, and validate the generalization ability of the proposed method in leveraging semantic information.

#### 4.1. Experimental Settings

**Dataset.** We use the KITTI 2015 [15] dataset with Eigen’s split [12] and Zhou’s [47] pre-preprocessing strategy, which leads to 39810 training images and 697 testing images. For the training of the semantic branch, we only use the pre-computed semantic maps from an off-the-shelf model [49] for supervision. The model is pre-trained on Cityscapes [8] (CS) and Mapillary Vistas dataset [28] (V). We mainly use the model fine-tuned on 200 KITTI (K) labeled images to generate the dataset SemCS+V+k. Consider the real-world scenarios, we also maintain another dataset SemCS+V without fine-tuning on KITTI, to validate the feasibility of using the precomputed labels trained from cross-domain datasets. We follow the practice of [48] to generate the binary semantic maps.

**Implementation Details.** We build our method on Monodepth2 [17] with ResNet-50 [20] pre-trained on the ImageNet [9] as backbone. The model is trained on a single NVIDIA Tesla V100 GPU with batch size of 12. The learning rate is set to $10^{-4}$ and divided by 10 for every 15 epochs. After the network converges, we select the model of epoch 20 for testing. The input image size is set to $192 \times 640$ following [17], and we compare our method with others on the same image resolution. We conduct online refinement following the practice of [3, 6, 48] with batch size of 1. The online refinement is performed 20 iterations on each test image, there is no data augmentation during this process. During testing, the network generates depth from the input image, and the semantic label is used to guide the feature alignment of the depth and semantic branches.

| Method          | Training | Abs Rel | Sq Rel | RMSE  | RMSElog | $\delta < 1.25$ | $\delta < 1.25^2$ | $\delta < 1.25^3$ |
|-----------------|----------|---------|--------|-------|---------|----------------|-----------------|-----------------|
| Zhou [47]       | M        | 0.183   | 1.595  | 6.709 | 0.270   | 0.734          | 0.902           | 0.959           |
| Mahjourian [27] | M        | 0.163   | 1.240  | 6.220 | 0.250   | 0.762          | 0.916           | 0.968           |
| GeoNet [45]     | M        | 0.155   | 1.296  | 5.857 | 0.233   | 0.793          | 0.931           | 0.973           |
| DDVO [37]       | M        | 0.151   | 1.257  | 5.583 | 0.228   | 0.810          | 0.936           | 0.974           |
| CC [32]         | M        | 0.140   | 1.070  | 5.326 | 0.217   | 0.826          | 0.941           | 0.975           |
| EPC++ [26]      | M        | 1.029   | 1.070  | 5.350 | 0.216   | 0.816          | 0.941           | 0.976           |
| GLNet [6]       | M        | 0.135   | 1.070  | 5.230 | 0.210   | 0.841          | 0.948           | 0.980           |
| Monodepth2 [17] | M        | 0.115   | 0.903  | 4.863 | 0.193   | 0.877          | 0.959           | 0.981           |
| PackNet [18]    | M        | 0.111   | 0.785  | 4.601 | 0.189   | 0.878          | 0.960           | 0.982           |
| Johnston [21]   | M        | 0.106   | 0.861  | 4.699 | 0.185   | 0.889          | 0.962           | 0.982           |
| Casser [3]      | M+Inst   | 0.141   | 1.026  | 5.291 | 0.215   | 0.816          | 0.945           | 0.979           |
| Chen [4]        | M+Sem    | 0.118   | 0.905  | 5.096 | 0.211   | 0.839          | 0.945           | 0.977           |
| Ochs [29]       | D+Sem    | 0.116   | 0.945  | 4.916 | 0.208   | 0.861          | 0.952           | 0.968           |
| Guizilini [19] - PackNet | M+Sem | 0.102 | 0.698 | 4.381 | 0.178 | 0.896 | 0.964 | 0.984 |
| Guizilini [19] - Res50 | M+Sem | 0.113 | 0.831 | 4.663 | 0.189 | 0.878 | 0.971 | 0.983 |
| Ours            | M+Sem    | 0.103   | 0.709  | 4.471 | 0.180   | 0.892          | 0.966           | 0.984           |
| Casser (+ref.) [3] | M+Inst | 0.109 | 0.825 | 4.750 | 0.187 | 0.874 | 0.958 | 0.983 |
| GLNet (+ref.) [6] | M   | 0.099   | 0.796  | 4.743 | 0.186   | 0.884          | 0.955           | 0.979           |
| Ours (+ref.)    | M+Sem    | 0.095   | 0.666  | 4.252 | 0.172   | 0.905          | 0.968           | 0.984           |

Table 1: Quantitative results on KITTI 2015. The best results are in bold and the second best results are underlined. “M” refer to self-supervision methods using monocular images only. “Inst” and “Sem” denote methods which leverage instance or semantic segmentation information. “-Res50” refers to the method which uses Resnet-50 as the backbone encoder. “+ref.” refers to self-supervision methods using monocular images only. “Inst” and “Sem” denote methods which leverage instance or semantic segmentation information.

For the training of the semantic branch, we only use the pre-computed semantic maps from an off-the-shelf model [49] for supervision. The model is pre-trained on Cityscapes [8] (CS) and Mapillary Vistas dataset [28] (V). We mainly use the model fine-tuned on 200 KITTI (K) labeled images to generate the dataset SemCS+V+k. Consider the real-world scenarios, we also maintain another dataset SemCS+V without fine-tuning on KITTI, to validate the feasibility of using the precomputed labels trained from cross-domain datasets. We follow the practice of [48] to generate the binary semantic maps.
4.2. Results on KITTI

We compare the proposed method with state-of-the-art monocular trained depth estimation methods on KITTI 2015 [15], the quantitative results are shown in Table 1. Note that the PackNet-based implementation of Guizilini et al. [19] is 0.102 in AbsRel. However, PackNet [18] alone takes more than 120M parameters for training, which is not applicable under certain circumstances with limited computation resources. Thus, we select the general Resnet-50 as backbone, which is also the same as our method for fair comparison. Our method outperforms state-of-the-art methods by a large margin on most evaluation metrics. The qualitative results are shown in Figure 5. The superiority of our method are illustrated in two aspects. Firstly, our method outperforms others in understanding depth from the category-level perspective. For instance, it successfully infers the correct depth on “train” and “traffic sign” area than other methods in the row 1 ~ 2 of Figure 5. Secondly, our method predicts high quality depth which is smooth inside object area (as the rider on row 3), and is sharp across the object borders (as the borders of people, cars and traffic signs in row 4 ~ 6). More results can be found in the supplementary material.

4.3. Ablation Study

We evaluate the effectiveness of the proposed modules in Table 2 by comparing the different versions of our method. We see that the baseline model performs the worst among all, and our proposed contributions improve consistently upon the baseline. When combined together, both contributions lead to a significant improvement of the performance.

4.4. Category-specific Depth Improvement

To further analysis the category-level improvements, we evaluate the improvement of depth predictions with respect to their semantic labels. Due to the absence of semantic groundtruth, we use the fine-tuned predicted labels $\text{Sem}_{CS+V+K}$ to specify the semantic area. We compare our method with the baseline model [17], with AbsRel as the evaluation metric. As shown in Figure 6, our method shows improvements towards most of the categories, including not only the foreground categories (traffic signs, person, cars, etc.), but also the background categories (sky, fence, wall, etc.) which can not be directly seen from the binary mask. It indicates that the semantic features provided by the binary mask are capable to offer rich contextual information with the guidance of the SSFA.

4.5. Performance on Noisy Semantic Labels

Due to the desperately lack of groundtruth semantic labels on real world scenarios, the noisy semantic inputs are inevitable during both training and testing phrase. We validate the effectiveness of our method in sampling point pairs across the real object borders (see Section 3.2.1). We use the pre-computed semantic label as guidance, and compare the proposed semantic-guided sampling strategy with the direct strategy which samples directly beside the edge points. We calculate the ratio of real cross-border points to all sampled pairs, using KITTI Semantics dataset [15] as
Table 2: Ablation experiments. We show the results of several ablated versions of our method on KITTI 2015 [15]. “SSFA” denotes the proposed SSFA scheme, and “SRL” refers to the semantic ranking loss. The best results are in bold.

| Method                  | SSFA | SRL | Abs Rel | Sq Rel | RMSE  | RMSE_{log} | \(\delta \leq 1.25\) | \(\delta \leq 1.25^2\) | \(\delta \leq 1.25^2\) |
|-------------------------|------|-----|---------|--------|-------|------------|----------------------|----------------------|----------------------|
| Baseline                | X    | X   | 0.110   | 0.830  | 4.639 | 0.187      | 0.884                | 0.962                | 0.982                |
| Baseline + SSFA         | ✓    | X   | 0.107   | 0.777  | 4.583 | 0.183      | 0.889                | 0.963                | 0.983                |
| Baseline + SRL          | X    | ✓   | 0.107   | 0.766  | 4.583 | 0.184      | 0.887                | 0.963                | 0.983                |
| Baseline + SSFA + SRL   | ✓    | ✓   | 0.103   | 0.709  | 4.471 | 0.180      | 0.892                | 0.966                | 0.984                |

Our sampling strategy improves upon the direct sampling groundtruth. The quantitative results are shown in Table 3. We show the results of several ablated versions of our method on KITTI 2015 [15]. “SSFA” denotes the proposed SSFA scheme, and “SRL” refers to the semantic ranking loss. The best results are in bold.

Table 3: The sampling accuracy of different strategies. Our semantic-guided sampling strategy outperforms the direct method by a significant margin of 19.9%.

| Sampling Strategy | Direct | The Proposed |
|-------------------|--------|--------------|
| Accuracy (%)      | 55.3   | 75.2         |

Figure 6: Category-specific depth improvement. We compare our method (blue) with the baseline (orange) using the metric of AbsRel. The rightmost is the average performance, which is the mean value of all categories’ performance. Our method improves consistently across most categories, including the foreground (person, rider, traffic sign, etc.) and the background (sky, fence, wall, etc.) classes.

Figure 7: Depth from erroneous segmentation labels. Despite different types of semantic degradation, our method still produce accurate depth maps.

Table 4: Performance on different datasets. The binary segmentation IoU (mIoU_{Bi}) differs a little across different datasets, and our model achieves comparable results on cross-domain generated semantic labels.

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Table 4: Performance on different datasets. The binary segmentation IoU (mIoU_{Bi}) differs a little across different datasets, and our model achieves comparable results on cross-domain generated semantic labels.

4.6. Study on Cross-domain Semantic Labels

Although fine-tuned only on 200 KITTI semantic labels, the generated semantic dataset Sem_{CS+V} is still guided by groundtruth information. To further validate the generalization ability, we train our model with semantic dataset Sem_{CS+V}, which is acquired from totally cross-domain trained semantic model. As shown in Table 4, we found an interesting phenomenon that although the full segmentation mIoU (mIoU_{Full}) of Sem_{CS+V} is obviously worse than that of Sem_{CS+V+K}, their binary mIoU (mIoU_{Bi}) is very close to each other (93.54% to 94.74%). It validates the advantage of the binary semantic maps, with which the performance of both semantic branch and semantic-guided sampling are less influenced by cross-domain predictions. At the meantime, our model trained on the cross-domain semantic dataset Sem_{CS+V} generalizes well, for its performance is only slightly behind with the one trained on Sem_{CS+V+K}, while still outperforms the state-of-the-art methods [18, 17, 21].

5. Conclusion

In this paper, we improve self-supervised depth estimation via leveraging both implicit and explicit semantic guidance. We propose a semantic-guided spatial feature alignment scheme to implicitly model the semantic category-level information for depth estimation. And we propose a semantic-guided ranking loss to explicitly constrain the depth map’s accuracy regarding to specific object categories. Extensive experiments show the superiority of the method. In future research, we plan to leverage the semantic information for depth refinement, to further improve the performance after the initial predictions.
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