Learning Occlusion-aware Coarse-to-Fine Depth Map for Self-supervised Monocular Depth Estimation

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ABSTRACT
Self-supervised monocular depth estimation, aiming to learn scene depths from single images in a self-supervised manner, has received much attention recently. In spite of recent efforts in this field, how to learn accurate scene depths and alleviate the negative influence of occlusions for self-supervised depth estimation, still remains an open problem. Addressing this problem, we firstly empirically analyze the effects of both the continuous and discrete depth constraints which are widely used in the training process of many existing works. Then inspired by the above empirical analysis, we propose a novel network to learn an Occlusion-aware Coarse-to-Fine Depth map for self-supervised monocular depth estimation, called OCFD-Net. Given an arbitrary training set of stereo image pairs, the proposed OCFD-Net does not only employ a discrete depth constraint for learning a coarse-level depth map, but also employ a continuous depth constraint for learning a scene depth residual, resulting in a fine-level depth map. In addition, an occlusion-aware module is designed under the proposed OCFD-Net, which is able to improve the capability of the learnt fine-level depth map for handling occlusions. Experimental results on KITTI demonstrate that the proposed method outperforms the comparative state-of-the-art methods under seven commonly used metrics in most cases. In addition, experimental results on Make3D demonstrate the effectiveness of the proposed method in terms of the cross-dataset generalization ability under four commonly used metrics. The code is available at https://github.com/ZM-Zhou/OCFD-Net_pytorch.

CCS CONCEPTS
- Computing methodologies → Scene understanding; Shape representations; Shape inference; Vision for robotics.

KEYWORDS
Monocular depth estimation, self-supervised learning, neural network

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1 INTRODUCTION
Monocular depth estimation, which aims to estimate scene depths from single images, is a challenging topic in the computer vision community. According to whether ground truth depths are given for model training, the existing methods for monocular depth estimation could be divided into two categories: supervised monocular depth estimation methods [2, 7–9, 22, 37] and self-supervised monocular depth estimation methods [10, 13, 15, 35, 43]. Since it is difficult and time-consuming to obtain high-quality and dense depths for large-scale outdoor scenes as ground truth, self-supervised monocular depth estimation has attracted more and more attention in recent years.

The existing works for self-supervised monocular depth estimation generally use either monocular video sequences [13, 43] or stereo image pairs [10, 15] as training data. At the training stage, the methods which are trained with video sequences do not only predict scene depths, but also estimate the camera poses, while the methods which are trained with stereo image pairs generally predict the pixel disparities between stereo pairs. Regardless of the types of training data, most of these methods focus on learning scene depths by introducing a continuous depth constraint (CDC) [10, 13, 16, 27, 35, 43], and recently, a few methods employ a discrete depth constraint (DDC) for pursuing scene depths [14, 15]. It is noted that in spite of rapid development for self-supervised monocular depth estimation, the following two problems still remain: (1) What are the advantage and disadvantage of both the CDC and DDC? (2) How to utilize the CDC and DDC more effectively to learn scene depth maps, particularly for occluded regions?

Addressing the two problems, we firstly empirically give an analysis on the effects of the CDC and DDC by utilizing two typical architectures, and we find that each of the two constraints has its own advantage and disadvantage. Then inspired by this analysis, a
novel network for self-supervised monocular depth estimation is proposed, which learns an Occlusion-aware Coarse-to-Fine Depth map, called OCFD-Net. The OCFD-Net is trained with stereo image pairs. It uses a DDC for learning a coarse-level depth map and a CDC for learning a scene depth residual, and then it outputs a fine-level depth map by integrating the obtained coarse-level depth map with the scene depth residual. In addition, we explore an occlusion-aware module under the proposed network, in order to strengthen the obtained fine-level depth map for resisting occlusions.

In sum, our main contributions include:

1) We empirically analyze the effects of the CDC and DDC, finding that a relatively higher prediction accuracy could be achieved by imposing the DDC, while a relatively smoother depth map could be obtained by imposing the CDC. This analysis could not only contribute to a better understanding of the depth constraints, but also give new insights into the design strategies for self-supervised monocular depth estimation.

2) We explore an occlusion-aware module, which is able to alleviate the negative influence of occluded regions on self-supervised monocular depth estimation.

3) Based on the aforementioned analysis on the effects of both CDC and DDC as well as the explored occlusion-aware module, we propose the OCFD-Net. It achieves better performances on the KITTI dataset than the comparative state-of-the-art methods in most cases as demonstrated in Section 4.

2 RELATED WORK

In this section, we review the self-supervised monocular depth estimation methods trained with monocular video sequences and stereo image pairs respectively.

2.1 Self-supervised monocular training

The existing methods which are trained with monocular video sequences simultaneously predict the scene depths and estimate the camera poses [1, 3, 5, 13, 16, 17, 20, 23, 30, 33, 39–41, 45]. Zhou et al. [43] proposed an end-to-end approach comprised of two separate networks for predicting depths and camera poses. Godard et al. [13] proposed the per-pixel minimum reprojection loss, the auto-mask loss, and the full-resolution sampling for self-supervised monocular depth estimation. Guizilini et al. [16] re-implemented upsample and downsample operations by 3D convolutions to preserve image details for depth predictions. Casser et al. [3] used instance segmentation maps to help model the object motions for handling the non-rigid scene problem. Additionally, the frameworks which jointly learnt depth, optical flow, and camera pose in a self-supervised manner were investigated in [5, 40].

2.2 Self-supervised stereo training

Unlike the methods trained with monocular video sequences, the existing methods which are trained with stereo image pairs generally estimate scene depths by predicting the disparities between stereo pairs [4, 10, 12, 26, 27, 31, 35, 36, 44]. Garg et al. [10] proposed a pioneering method, which reconstructed one image of a stereo pair with the other image using the predicted depths at its training stage. Godard et al. [12] presented a left-right disparity consistency loss to improve the robustness of the proposed method. To handle the occlusion problem, Poggi et al. [27] proposed the 3Net which was trained in a trinocular domain, while different types of occlusion masks were proposed in [36, 44] for indicating the occlusion regions. Additionally, several methods used extra supervision information (e.g. disparities generated with Semi Global Matching [31, 35, 44], semantic segmentation labels [4, 44]) to improve the performance of self-supervised monocular depth estimation. It is noted that all the aforementioned methods employed a continuous depth constraint (CDC) for depth estimation at their training stage, assuming that the disparity of each pixel is a continuous variable determined by the visual consistency between the input training stereo images.

Unlike the above methods that utilized the CDC, a few methods [14, 15] employed a discrete depth constraint (DDC) at their training stage, assuming that the depth of each pixel is inversely proportional to a weighted sum of a set of discrete disparities determined by the visual consistency between the input training stereo images. Gonzalez and Kim [15] proposed a self-supervised monocular depth estimation network by utilizing the DDC with a mirrored exponential disparity discretization.

3 METHODOLOGY

In this section, we propose the OCFD-Net for self-supervised monocular depth estimation. Firstly, we give an empirical analysis on the effects of the continuous depth constraint (CDC) and discrete depth constraint (DDC) used in literature. Then according to this analysis, we describe the proposed OCFD-Net in detail.

3.1 Effects of CDC and DDC

As discussed in Section 2, most of the existing methods which are trained with stereo images learn depths by introducing either the CDC [10, 12, 13, 16, 26, 27, 35, 43] or the DDC [14, 15]. However, it is still unclear what are the advantage and disadvantage of the CDC in comparison to the DDC. Addressing this issue, we investigate the effects of the two depth constraints empirically here.

Specifically, under each of the two depth constraints, we evaluate the following two typical backbone architectures which are used in many existing self-supervised monocular depth estimation methods (rather than these original methods) on the KITTI dataset [11] with the raw Eigen splits [7], in order to concentrate on the two constraints and simultaneously avoid possible disturbances of other modules involved in these original methods:

**FAL-Arc**: It has a 21-layer convolutional architecture as used in the DDC-based FAL-Net [15] and PLADE-Net [14].

**Res-Arc**: It has a ResNet-50 [18] based architecture as used in many CDC-based works, e.g. [12, 13, 27, 35, 44].

The corresponding results are reported in Table 1 (the metrics are introduced in Section 4). As is seen, both the two architectures with DDC outperform those with CDC under all the metrics, demonstrating that DDC is probably more helpful for boosting the performances of the existing methods.

In addition, the visualization results of the estimated depth maps by the two architectures with the two depth constraints are shown in Figure 1. Two points are revealed from this figure: (1) The depth maps estimated by the two architectures with DDC preserve more detailed information than those with CDC (e.g. the estimated depths on the cylindrical objects by the two architectures with DDC are
Table 1: Quantitative comparison of FAL-Arc and Res-Arc with CDC and DDC on the raw KITTI Eigen test set [7]. ↓ / ↑ denotes that lower / higher is better.

| Arc       | Constraint | Abs Rel ↓ | Sq Rel ↓ | RMSE ↓ | logRMSE ↓ | A1 ↑ | A2 ↑ | A3 ↑ |
|-----------|------------|-----------|----------|--------|-----------|------|------|------|
| FAL-Arc   | CDC        | 0.135     | 0.915    | 4.705  | 0.212     | 0.834| 0.937| 0.975|
| FAL-Arc   | DDC        | 0.104     | 0.683    | 4.363  | 0.190     | 0.877| 0.960| 0.981|
| Res-Arc   | CDC        | 0.126     | 0.912    | 4.592  | 0.204     | 0.851| 0.944| 0.977|
| Res-Arc   | DDC        | 0.112     | 0.685    | 4.298  | 0.193     | 0.871| 0.957| 0.981|

3.2 OCFD-Net

Here, we propose the OCFD-Net, whose architecture is shown in Figure 2(a). It is trained with stereo image pairs, and it has a coarse-to-fine depth module, an image reconstruction module, and an occlusion-aware module. Considering the relative advantage of DDC for improving estimation accuracy, the coarse-to-fine depth module learns a coarse-level depth map under the imposed DDC by the image reconstruction module, which could provide a relatively accurate initial estimation of depth. And considering the relative advantage of CDC for maintaining the smoothness of the estimated depths, the coarse-to-fine depth module learns a scene depth residual for providing a smooth depth compensation under the imposed CDC by the image reconstruction module, then it learns a fine-level depth map by integrating the obtained coarse-level depth map with the scene depth residual. Additionally, the occlusion-aware module is designed for alleviating the negative influence of occluded regions. We introduce the three modules and the used loss function as follows:

3.2.1 Coarse-to-fine depth module. The coarse-to-fine depth module is to learn a fine-level depth map by simultaneously learning a coarse-level depth map and a scene depth residual from an input scene image. It has a backbone sub-network for feature extraction, a coarse-level depth prediction branch, and a depth residual prediction branch, as shown in Figure 2(b).

Backbone sub-network. It employs an encoder-decoder architecture for extracting a visual feature \( F^l \in \mathbb{R}^{W \times H \times C_f} \) from the input left image \( I^l \in \mathbb{R}^{W \times H \times C} \), where \( \{W, H\} \) are the height and width of the image, and \( C_f \) is the number of feature channels. Similar to [12, 13, 27], this backbone sub-network simply uses the first five blocks of ResNet50 [18] as its encoder, and the 5-block decoder designed in [13] as its decoder. In addition, a DenseASPP module [38] with dilation rates \( r \in \{3, 6, 12, 18, 24\} \) is inserted between the first two blocks of the decoder to extract a multi-scale feature.

Coarse-level depth prediction branch. It uses the feature \( F^l \) extracted from the backbone sub-network as its input, and pursues a coarse-level depth map \( D^l \) for the left image by imposing the DDC. This branch consists of a \( 3 \times 3 \) convolutional layer with \( N \) channels, a softmax operation, and a disparity-depth transformation layer. The convolutional layer maps the feature \( F^l \) to a density volume \( V_d^l = [V_d^l]_{n=0}^{N-1} \), where \( V_d^l \in \mathbb{R}^{W \times H \times 1} \) is the \( n \)th channel of \( V_d^l \) and \( [\cdot]_n \) denotes a concatenation operation along the third dimension. Then, a probability volume \( V_p^l = [V_p^l]_{n=0}^{N-1} \) is obtained by passing \( V_d^l \) through the softmax operation along the third dimension.

Given a disparity range \( [d_{\text{min}}, d_{\text{max}}] \) where \( d_{\text{min}} \) and \( d_{\text{max}} \) are the predefined minimum and maximum disparities respectively, a...
Figure 2: Architectures of OCFD-Net and its coarse-to-fine depth module. (a) Architecture of OCFD-Net. It has a coarse-to-fine depth module, an image reconstruction module, and an occlusion-aware module. ‘⊕’ denotes the element-wise addition and ‘⊙’ denotes the element-wise multiplication. (b) Architecture of the coarse-to-fine depth module. ‘Conv-3x3, N’ denotes a $3 \times 3$ convolutional layer with $N$ channels, and ‘⊗’ denotes the scalar multiplication.

set of discrete disparity values $\{d_n\}$ is generated by the mirrored exponential disparity discretization [15] as:

$$d_n = d_{\text{max}} \left( \frac{d_{\text{min}}}{d_{\text{max}}} \right)^{\frac{n}{N-1}}, \quad n = 0, 1, ..., N - 1.$$  (1)

According to the described DDC in Section 2.2 as well as the obtained probability volume $V_{lp}$ above, a disparity map $\hat{d}_c$ for the left image is obtained by calculating a weighted sum of $\{d_n\}_{n=0}^{N-1}$ with the corresponding weights $\{V_{lpn}\}_{n=0}^{N-1}$:

$$\hat{d}_c = \sum_{n=0}^{N-1} V_{lpn} d_n.$$  (2)

According to the obtained $\hat{d}_c$, our coarse-level depth map $D_c$ for the left image is calculated via the following operation at the disparity-depth transformation layer:

$$D_c = \frac{B f_x}{\hat{d}_c},$$  (3)

where $B$ is the baseline length of the stereo pair and $f_x$ is the horizontal focal length of the left camera.

Residual depth prediction branch. It uses the feature $F_l$ extracted from the backbone sub-network as its input, and outputs a scene depth residual $D_{res}^l$ in $\mathbb{R}^{W \times H \times 1}$ for the left image by imposing the CDC for refining the coarse-level depth $D_c$. This branch consists of a $3 \times 3$ convolutional layer with 1 channel, a sigmoid operation used as the activation function, and a residual adjustment layer. A feature residual map $F_{res}^l$ whose elements vary in $[0, 1]$ is firstly calculated by passing the feature $F_l$ through the convolutional layer with the sigmoid activation. Then, considering that a depth residual should be able to provide an either positive or negative compensation for the coarse-level depth map predicted from the coarse-level depth prediction branch, the feature residual $F_{res}^l$ is transformed into a range $[-0.5w, 0.5w]$ (where $w$ is a preset compensation parameter) via the following linear transformation at the residual adjustment layer:

$$D_{res}^l = w (F_{res}^l - 0.5).$$  (4)

Once the scene depth residual $D_{res}^l$ and the coarse-level depth map $D_c$ are obtained, a fine-level depth map $D_f^l$ is obtained as:

$$D_f^l = D_c + D_{res}^l.$$  (5)

3.2.2 Image reconstruction module. The image reconstruction module uses one image from each input stereo pair to reconstruct its partner with the predicted depth maps for network training. As shown in Figure 2(a), this module contains two parts: a discrete reconstruction block for imposing the DDC and a continuous reconstruction block for imposing the CDC.

Discrete reconstruction block. It takes the left image $I_l$ and the predicted density volume $V_{lp} = [V_{lpn}]_{n=0}^{N-1}$ as its input, and it reconstructs the right image under the DDC. As done in [15], the density volume $V_{dr} = [V_{drn}]_{n=0}^{N-1}$ for the right view is firstly generated by
shifting each channel \( V^l_{dn} \) of \( V^l_d \) with the disparity \( d_n \). Then, \( \hat{V}^l_d \) is passed through a softmax operation along the third dimension to obtain the right-view probability volume \( \hat{V}^r_p = [\hat{V}^r_{pn}]_{n=0}^{N-1} \). According to the DDC, the reconstructed right image \( \hat{r} \) is obtained by calculating a weighted sum of the shifted \( N \) versions of the left image \( \hat{l} \) with the corresponding probabilities \( \hat{V}^r_{pn} \):

\[
\hat{r} = \sum_{n=0}^{N-1} \hat{V}^r_{pn} \circ \hat{l}^l_n ,
\]

where \( \odot \) denotes the element-wise multiplication, and \( l^l_n \) is the left image shifted with \( d_n \).

**Continuous reconstruction block.** It takes the right image \( r \) and the fine-level depth map \( D^l_f \) as its input, and it reconstructs the corresponding left image under the CDC. Specifically, for an arbitrary pixel coordinate \( p \in \mathbb{R}^2 \) in the left image, its corresponding coordinate \( p' \) in the right image is obtained with the fine-level depth map \( D^l_f \):

\[
p' = p - \frac{B f_x}{D^l_f(p)} \circ \hat{l}^l_1 .
\]

Accordingly, the reconstructed left image \( \hat{l}^l_1 \) is obtained by assigning the RGB value of the right image pixel \( p' \) to the pixel \( p \) of \( \hat{l}^l_1 \).

### 3.2.3 Occlusion-aware module

As shown in Figure 2(a), the explored occlusion-aware module contains a probability-volume-based mask builder and a disparity-map-based mask builder for learning two masks \( M^l_o \) and \( M^l_m \). The two masks have the same size as the input images, and each element in them varies from 0 to 1 and indicates the probability of whether the corresponding pixel in the left view image is still visible in the right view. Then, the occlusion-aware module builds an occlusion mask \( M^l_{occ} \) by element-wisely multiplying \( M^l_o \) with \( M^l_m \):

**Probability-volume-based mask builder.** This builder takes the probability volume \( \hat{V}^r_p \) (obtained by the discrete reconstruction block) as its input, and it builds a probability-volume-based mask \( M^l_o \) as done in [15]. Under the DDC, a cyclic probability volume \( \hat{V}^{r-l}_{p} \) is obtained by shifting \( \hat{V}^r_p \) back into the left view. Accordingly, for each pixel that is visible in the left view but invisible in the right view, its corresponding elements in all the channels of \( \hat{V}^{r-l}_{p} \) should be equal or close to 0 in the ideal or noisy case. For each pixel that is visible in both the two views, its corresponding element in some one of the \( N \) channels of \( \hat{V}^{r-l}_{p} \) should be much larger than 0. Hence, the probability-volume-based mask is defined as:

\[
M^l_o = \min \left( \sum_{n=0}^{N-1} \hat{V}^{r-l}_{pn} , 1 \right) .
\]

**Disparity-map-based mask builder.** This builder takes the coarse-level disparity map \( d^c \) as its input, and it builds a disparity-map-based mask \( M^l_m \) based on the following observation: for an arbitrary pixel location \( p = [x_p, y_p]^\top \) and its horizontal right neighbor \( p_i = [x_p + 1, y_p]^\top \), the difference between their disparities \( d^c(p) \) and \( d^c(p_i) \) should be close or equal to the difference of their horizontal coordinates [44]. Hence, this mask builder is formulated as:

\[
M^l_m(p) = \min \left( \min_{i} \left( \frac{d^c(p) - d^c(p_i)}{1} \right) , 1 \right) .
\]

### 3.2.4 Loss function

The total loss function for training the OCFD-Net contains the following 4 loss terms:

**Coarse-level reconstruction loss \( L_{CR} \).** As done in [15], it is formulated as a weighted sum of the \( L_1 \) loss and the perceptual loss [19] for reflecting the similarity between the reconstructed left image \( \hat{l} \) and the input right image \( l' \):

\[
L_{CR} = \| \hat{l} - l' \|_1 + \alpha_1 \sum_{i=1,2,3} \| f^l_{R18}(\hat{l}^r) - f^l_{R18}(l'^r) \|_2 ,
\]

where \( \| \cdot \|_1 \) and \( \| \cdot \|_2 \) represent the \( L_1 \) norm and the \( L_2 \) norm, \( f^l_{R18}(\cdot) \) denotes the output of the \( i^{th} \) block of ResNet18 [18] pretrained on the ImageNet dataset [28], and \( \alpha_1 \) is a tuning parameter.

**Fine-level reconstruction loss \( L_{FR} \).** It is formulated as a weighted sum of the \( L_1 \) loss and the structural similarity (SSIM) loss [34] for reflecting the photometric difference between the reconstructed left image \( \hat{l} \) and the input left image \( l \), with the occlusion mask \( M^l_{occ} \) for alleviating the negative influence of occlusions and the edge mask \( M^l_{edge} \) [23] for filtering out the pixels whose reprojected coordinates are out of the image:

\[
L_{FR} = M^l_{occ} \odot M^l_{edge} \odot \left( \alpha_2 \| \hat{l} - l \|_1 + (1 - \alpha_2) \text{SSIM}(\hat{l}, l) \right) ,
\]

where \( \alpha_2 \) is a balance parameter.

**Coarse-level smoothness loss \( L_{CS} \) and fine-level smoothness loss \( L_{FS} \).** As done in [12, 15], we adopt the edge-aware smoothness loss to constrain the continuity of both the coarse-level and fine-level disparity maps. The coarse-level smoothness loss is formulated as:

\[
L_{CS} = \| \partial_x^c \hat{d}^c_l \|_1 e^{-\beta_x \| \partial_x^c \hat{d}^c_l \|_1} + \| \partial_y^c \hat{d}^c_l \|_1 e^{-\beta_y \| \partial_y^c \hat{d}^c_l \|_1} ,
\]

where \( \partial_x^c \) and \( \partial_y^c \) are the differential operators in the horizontal and vertical directions respectively, and \( \beta_x \) and \( \beta_y \) are parameters for adjusting the degree of edge preservation. The fine-level smoothness loss uses an additional weight matrix \( W = 1 + (1 - M^l_{occ} \odot M^l_{edge}) \) to enforce the smoothness in occluded and edge regions as:

\[
L_{FS} = W \odot \left( \| \partial_x \hat{d}^c_l \|_1 e^{-\beta_x \| \partial_x \hat{d}^c_l \|_1} + \| \partial_y \hat{d}^c_l \|_1 e^{-\beta_y \| \partial_y \hat{d}^c_l \|_1} \right) ,
\]

where \( \beta_e \) is the edge preservation parameter.

Finally, the total loss is a weighted sum of the above four loss terms, which is formulated as:

\[
L = L_{CR} + \lambda_1 L_{FR} + \lambda_2 L_{CS} + \lambda_3 L_{FS} ,
\]

where \( \lambda_1, \lambda_2, \lambda_3 \) are three preset weight parameters.

### 4 EXPERIMENTS

#### 4.1 Datasets and metrics

We train OCFD-Net on the KITTI dataset [11] with the Eigen split [7], which consists of 22600 stereo image pairs. Additionally, the Cityscapes dataset [6], which consists of 22972 stereo pairs, is used for jointly training OCFD-Net as done in [15]. The raw and
Table 2: Quantitative comparison on both the raw and improved KITTI Eigen test sets. The best and the second best results are in bold and underlined in each metric.

| Method               | PP. | Data. | Sup. | Abs Rel ↓ | Sq Rel ↓ | RMSE ↓ | logRMSE ↓ | A1 ↑ | A2 ↑ | A3 ↑ |
|----------------------|-----|-------|------|-----------|----------|--------|-----------|------|------|------|
| Raw Eigen test set [7]|     |       |      |           |          |        |           |      |      |      |
| Zhao et al. [41]     | K   | M     |      | 0.139    | 1.034    | 5.264  | 0.214     | 0.821| 0.942| 0.978|
| DualNet [42]         | K   | M     |      | 0.121    | 0.837    | 4.945  | 0.197     | 0.853| 0.955| 0.982|
| PackNet [16]         | K   | M     |      | 0.107    | 0.802    | 4.538  | 0.186     | 0.889| 0.962| 0.981|
| Johnston and Carneiro [20] | K   | M     |      | 0.106    | 0.861    | 4.699  | 0.185     | 0.889| 0.962| 0.982|
| Shu et al. [30]      | K   | M     |      | 0.104    | 0.729    | 4.481  | 0.179     | 0.893| 0.965| 0.984|
| sNet [27]            | ✓   | K     | S    | 0.126    | 0.961    | 5.205  | 0.220     | 0.835| 0.941| 0.974|
| Peng et al. [25]     | ✓   | K     | S    | 0.107    | 0.908    | 4.877  | 0.202     | 0.862| 0.945| 0.975|
| monodepth2 [15]      | ✓   | K     | S(d) | 0.111    | 0.867    | 4.714  | 0.199     | 0.864| 0.954| 0.979|
| Monodepth2 [15]      |     | K     | S    | 0.107    | 0.849    | 4.764  | 0.201     | 0.874| 0.953| 0.977|
| Pinzer et al. [26]   |     | K     | S    | 0.098    | 0.831    | 4.656  | 0.202     | 0.882| 0.948| 0.973|
| DepthHints [35]      | ✓   | K     | S(d) | 0.096    | 0.710    | 4.393  | 0.185     | 0.890| 0.962| 0.981|
| FAL-Net [15]         | ✓   | K     | S    | 0.093    | 0.564    | 3.973  | 0.174     | 0.898| 0.967| 0.985|
| Zhu et al. [44]      | ✓   | K     | S(s,d)| 0.096   | 0.646    | 4.244  | 0.177     | 0.898| 0.966| 0.983|
| PLADE-Net [14]       | ✓   | S     | K    | 0.089    | 0.590    | 4.008  | 0.172     | 0.900| 0.967| 0.985|
| OCFD-Net (our)       | ✓   | K     | S    | 0.091    | 0.576    | 4.036  | 0.174     | 0.901| 0.967| 0.984|
| OCFD-Net (our)       | ✓   | K     | S    | 0.090    | 0.563    | 4.005  | 0.172     | 0.903| 0.967| 0.984|
| Improved Eigen test set [32]|     |       |      |           |          |        |           |      |      |      |
| Zhao et al. [41]     | CS+K| M     |      | 0.153    | 1.026    | 5.153  | 0.210     | 0.833| 0.945| 0.979|
| PackNet [16]         | CS+K| M     |      | 0.104    | 0.758    | 4.386  | 0.182     | 0.895| 0.964| 0.982|
| Guizilini et al. [17]| CS+K| M(s)  |      | 0.100    | 0.761    | 4.270  | 0.175     | 0.902| 0.965| 0.982|
| sNet [27]            | ✓   | CS+K  | S    | 0.111    | 0.849    | 4.822  | 0.202     | 0.865| 0.952| 0.978|
| Peng et al. [25]     | ✓   | CS+K  | S    | 0.100    | 0.767    | 4.455  | 0.189     | 0.881| 0.956| 0.980|
| monodepthMatch [31]  | ✓   | CS+K  | S(d) | 0.096    | 0.673    | 4.351  | 0.184     | 0.890| 0.961| 0.981|
| FAL-Net [15]         | ✓   | CS+K  | S    | 0.088    | 0.547    | 4.004  | 0.175     | 0.898| 0.966| 0.984|
| PLADE-Net [14]       | ✓   | CS+K  | S    | 0.087    | 0.550    | 3.837  | 0.167     | 0.908| 0.970| 0.985|
| OCFD-Net (our)       | ✓   | CS+K  | S    | 0.088    | 0.554    | 3.944  | 0.171     | 0.906| 0.967| 0.984|
| OCFD-Net (our)       | ✓   | CS+K  | S    | 0.086    | 0.536    | 3.889  | 0.169     | 0.909| 0.969| 0.985|

For the evaluation on the KITTI dataset [11] (also jointly trained with the Cityscapes dataset [11]), we use the following metrics as done in [12, 13, 15, 43]: Abs Rel, Sq Rel, RMSE, logRMSE, \( A_1 = \delta < 1.25 \), \( A_2 = \delta < 1.25^2 \), and \( A_3 = \delta < 1.25^3 \). For the evaluation on Make3D [29], we use the following metrics as done in [12, 13, 15]: Abs Rel, Sq Rel, RMSE, and \( \log_{10} \).

4.2 Implementation details

We implement the OCFD-Net with PyTorch [24]. The encoder of the backbone sub-network is pretrained on the ImageNet dataset [28]. For disparity discretization, we set the minimum and the maximum disparities to \( d_{\text{min}} = 2, d_{\text{max}} = 300 \), and the number of the discrete levels is set to \( N = 49 \). The weight of the scene depth residual is set to \( w = 10 \), and we set \( K = 41 \) for the disparity-map-based mask. The weight parameters for the loss function are set to \( \lambda_1 = 1, \lambda_2 = 0.0008 \), and \( \lambda_3 = 0.001 \), while we set \( \alpha_1 = 0.1, \alpha_2 = 0.15, \beta_k = 2 \) and \( \beta_2 = 1 \). The Adam optimizer [21] with \( \beta_1 = 0.5 \) and \( \beta_2 = 0.999 \) is used to train the OCFD-Net for 50 epochs with a batch size of 8. The initial learning rate is firstly set to \( 10^{-4} \), and is downgraded by half at epoch 30 and 40. The on-the-fly data augmentations are performed in training, including random resizing (from 0.75 to 1.5).

improved KITTI Eigen test sets [7] are used to evaluate OCFD-Net, which consist of 697 and 652 images respectively. At both the training and inference stages, the images are resized into the resolution of \( 1280 \times 384 \), while we assume that the intrinsics of all the images are identical. We also test OCFD-Net on the Make3D [29] test set, which includes 134 images. At the inference stage on Make3D, we crop and resize the input images as done in [13].
We firstly evaluate the OCFD-Net with/without a post-processing step. Table 3: Quantitative comparison on Make3D [29]. Note that all the methods benefit from the median scaling. The methods marked with ‘+PP.’ benefit from the post-processing step.

| Method               | Sup. | Abs Rel | Sq Rel | RMSE | log10 |
|----------------------|------|---------|--------|------|-------|
| DDVO [35]            | M    | 0.387   | 4.720  | 8.090| 0.204 |
| Monodepth2 [13]      | M    | 0.322   | 3.589  | 7.147| 0.163 |
| Johnston and Carneiro[20] | M   | 0.297   | 2.902  | 7.013| 0.158 |
| FAL-Net + PP. [15]   | S    | 0.284   | 2.803  | 6.643| -     |
| PLADE-Net + PP. [14] | S    | 0.265   | 2.469  | 6.373| -     |
| PLADE-Net(CS+K) + PP. [14] | S | 0.253   | 2.100  | 6.031| -     |
| OCFD-Net             | S    | 0.279   | 2.573  | 6.421| 0.145 |
| OCFD-Net + PP.       | S    | 0.275   | 2.515  | 6.354| 0.144 |
| OCFD-Net(CS+K) + PP. | S    | 0.256   | 2.187  | 5.856| 0.135 |

As seen from Table 2, when only the KITTI dataset [11] is used for training (K), our OCFD-Net without post processing outperforms the comparative methods without post processing under all the evaluation metrics. The performance of our method is improved by adopting the post processing step, which simply averages the depths of the input image and the flipped depths of a flipped copy of the image. And our method performs best under 4 metrics and second-best under the other 3 metrics on the raw KITTI Eigen test set [7]. When both Cityscapes [6] and KITTI [11] are jointly used for training (CS+K) as done in [14–17, 27, 31, 41], the performance of OCFD-Net is further boosted. On the improved KITTI Eigen test set [32], our method performs better than all the comparative methods in most cases. These results demonstrate that the OCFD-Net is able to achieve more effective depth estimation.

In Figure 3, we also give several visualization results of OCFD-Net as well as two comparative methods, DepthHints [35] and FAL-Net [15], which perform without extra semantic supervision as done in our method and achieve better performances than the other comparative methods in most cases. Their visualization results are generated with their open-source pretrained models. It can be seen that DepthHints predicts inaccurate depths on the regions close to object boundaries (first row of Figure 3), FAL-Net predicts unsmooth depths on the flat regions (second row of Figure 3), but our OCFD-Net could handle both the two cases effectively. As seen from the yellow rectangle in the last row of Figure 3, all the three methods generate unreliable depths on the black region, indicating that it is still hard for them to handle texture-less regions, and it would be one of our future works to improve the proposed method for handling texture-less regions more effectively.

Furthermore, we train the OCFD-Net on KITTI [11] (or on both KITTI and Cityscapes [6]) and evaluate it on Make3D [29] for testing its cross-dataset generalization ability. The corresponding results of the OCFD-Net and 5 comparative methods [13–15, 20, 33] are reported in Table 3, where the results of these methods are cited from their original papers. It can be seen that the OCFD-Net outperforms 4 comparative methods and is competitive with the state-of-the-art PLADE-Net [14], demonstrating its generalization ability on the unseen dataset. Several visualization results on Make3D shown in Figure 4 further demonstrate that the OCFD-Net could estimate scene depths effectively and maintain detailed structures of scenes.

and cropping (640×192), random horizontal flipping, and random color augmentation.

4.3 Comparative evaluation

We firstly evaluate the OCFD-Net with/without a post-processing step (PP.) [12] on the raw KITTI Eigen test set [7] in comparison to 15 state-of-the-art methods, including 6 methods trained with monocular video sequences (M) [16, 17, 20, 30, 41, 42] and 9 methods trained with stereo image pairs (S) [13–15, 25–27, 31, 35, 44]. As done in [14–16], we also evaluate the OCFD-Net on the improved KITTI Eigen test set [32]. The corresponding results by all the referred methods are cited from their original papers and reported in Table 2. It is noted that some methods are trained with additional supervision, such as the semantic segmentation label (s) [17, 44], and the offline computed disparity (d) [31, 35, 44].
### 4.4 Ablation studies

This subsection verifies the effectiveness of each key element in OCFD-Net by conducting ablation studies on the KITTI dataset [11]. We firstly train a simplest version of OCFD-Net (denoted as Base-line), consisting of the proposed backbone sub-network and the coarse-level depth prediction branch. Then, we sequentially add the Depth Residual prediction Branch (DRB), the probability-volume-based mask ($M_{l_v}$), and the disparity-map-based mask ($M_{lm}$) into the model.

The results are reported in Table 4. It is noted that 'Baseline+DRB' performs better than 'Baseline' under 4 metrics, probably because the DRB improves the smoothness of the estimated depths on flat regions, but it performs poorer under the metric 'Sq Rel', mainly because the depths of occluded regions are simultaneously wrongly smoothed, as illustrated by the corresponding visualization result in the left column of Figure 5. Additionally, by singly utilizing the occlusion mask $M_{l_v}$ (also $M_{lm}$), the depth estimation accuracy is further improved. Our full model (OCFD-Net) with $M_{occ}$ could detect occluded regions effectively, as illustrated on the bottom left of Figure 5, and it performs best under all the metrics.

To further understand the effect of the depth residual prediction branch, we visualize the depth maps and the residual map generated by OCFD-Net in the right column of Figure 5. It can be seen that the intensities of the depth residual map $D_{res}$ are large on the relatively far regions, and the enlarged versions of the yellow rectangle regions further show that a smoother fine-level depth map $D_f$ is obtained by integrating $D_{res}$ with the coarse-level depth map $D_c$.

We also evaluate the influence of the residual weight $w$ in Equation (4) by training the OCFD-Net with $w = \{1, 5, 10, 20, 100\}$ respectively. The corresponding results are reported in Table 5. As seen from this table, when $w$ ranges from 5 to 20, the corresponding results are close, and the OCFD-Net with $w = 10$ achieves a trade-off among all the evaluation metrics. It demonstrates that the performance of OCFD-Net is not sensitive to the residual weight $w$.

### 5 CONCLUSION

In this paper, we propose the OCFD-Net for self-supervised monocular depth estimation. Firstly, we empirically find that both the discrete and continuous depth constraints widely used in literature have their own advantage and disadvantage: the discrete depth constraint is relatively more effective for improving estimation accuracy, while the continuous one maintains relatively better depth smoothness. Inspired by this finding, we design the OCFD-Net to learn a coarse-to-fine depth map with stereo image pairs by jointly utilizing both the continuous and discrete depth constraints.

Moreover, we explore an occlusion-aware module for handling occlusions under the OCFD-Net. Experimental results show the effectiveness of the proposed OCFD-Net.

In the future, we will further investigate how to make use of both the continuous and discrete constraints more effectively for improving depth estimation accuracy, as well as how to effectively handle texture-less regions as indicated in Section 4.3.

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