Boosting Monocular Depth Estimation with Sparse Guided Points*

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Abstract

Existing monocular depth estimation shows excellent robustness in the wild, but the affine-invariant prediction requires aligning with the ground truth globally while being converted into the metric depth. In this work, we firstly propose a modified locally weighted linear regression strategy to leverage sparse ground truth and generate a flexible depth transformation to correct the coarse misalignment brought by global recovery strategy. Applying this strategy, we achieve significant improvement (more than 50% at most) over most recent state-of-the-art methods on five zero-shot datasets.

Moreover, we train a robust depth estimation model with 6.3 million data and analyze the training process by decoupling the inaccuracy into coarse misalignment inaccuracy and detail missing inaccuracy. As a result, our model based on ResNet50 even outperforms the state-of-the-art DPT ViT-Large model with the help of our recovery strategy. In addition to accuracy, the consistency is also boosted for simple per-frame video depth estimation. Compared with monocular depth estimation, robust video depth estimation, and depth completion methods, our pipeline obtains state-of-the-art performance on five zero-shot datasets.

To leverage the precious ground truth and enhance the performance, we first analyze the error map between the ground truth and aligned prediction depth, and observe that the error can be decoupled into two parts: the coarse misalignment error and detail missing error. The latter can only be alleviated by supervision during training or optimization during post-processing, but the former can be reduced by fitting the distribution of prediction depth and ground truth more flexibly.

In this work, we propose to quantitatively decouple the above-mentioned inaccuracy and alleviate the coarse misalignment error by fitting a depth transformation with sparse ground-truth depth through a modified locally weighted linear regression strategy. Compared with traditional linear regression, the proposed strategy can leverage the robust depth prior of monocular depth estimation and the distribution of ground truth to improve the performance. Ablation study shows our strategy is robust to both the amount and randomly-generated noises of the ground truth, which can also perform well with ground-truth obtained from cost-effective sensors and even some traditional geometric algorithm such as triangulation.

Besides leveraging sparse ground truth, the robustness of monocular depth estimation can also bring a precise prior, boost the performance, and reduce the demand for sparse points. Therefore, a robust model trained with 6.3 Million data is proposed and analyzed in our experiments. With the robust data-driven model, modified recovery strategy, and sparse guided points, a novel pipeline for video depth estimation is proposed by simply predicting per-frame depth and aligning with a sparse set of ground-truth depth values.

To summarize, our main contributions are as follows:

- A novel metric depth recovery strategy that can significantly improve the performance of consistency and accuracy but only requires sparse guided depth.

1. Introduction

Dense monocular depth estimation [29, 30, 54] is a significant task and can be helpful in many fields such as autonomous driving [42], virtual reality (VR) [18], augmented reality (AR), and 3D scene reconstruction [49]. Despite the excellent robustness of monocular depth estimation in the wild, existing state-of-the-art methods can only predict affine-invariant depth with unknown scale and shift, which requires aligning with the ground truth through global least-square fitting.

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• An effective tool based on scale recovery to visualize and quantify monocular depth errors caused by coarse misalignment and missing details, respectively.
• A robust monocular depth estimation model trained on diverse dataset collectives of 6.3 Million images in total, together with detailed analysis of its performance w.r.t. the training dataset size using our analytics tool.
• A pipeline for consistent and accurate video depth estimation, assisted with very sparse depth information.
• With our local scale and shift recovery method, we systematically analyze the error distribution for depth estimation in many settings, including single image depth estimation, depth completion and video depth estimation methods and show consistent precision gain.
• Experiments are conducted to apply modified local recovery strategy to state-of-the-art monocular depth estimation methods, bringing more than 50% improvement in performance over all state-of-the-art methods.

With the proposed strategy, our ResNet50 model even outperforms DPT [29] with the ViT-Large [10] backbone. For video depth estimation, our pipeline significantly improves both the accuracy and consistency, and achieves state-of-the-art on five NYU [34] videos. 3D scene reconstructions from consistent video depth estimation are also conducted for intuitive comparison.

2. Related Work

Monocular Depth Estimation. Monocular depth estimation is an important problem. Through training a dataset individually, many methods [20, 21, 52] have achieved promising results. However, the resulting models generalize poorly to diverse scenes. To mitigate this problem, Chen et al. [2] constructed the first large-scale and diverse dataset (DIW), and enforced the network to learn depth ordering relations, termed relative depth. As very sparse paired points are annotated in each image, several approaches [2, 4, 22, 43, 44] propose to obtain the ground truth of dense relative depth by leveraging the online web-stereo videos or images. Owing to large-scale and diverse data samples, these strategies can produce a model with strong generalization.

Although learning relative depth can obtain a robust model, the relative depth can only represent ordinal depth relations and loses the geometry information, i.e., one point is farther or closer than another one. Therefore, some works [30, 51, 53, 54] proposed to learn affine-invariant depth. Ranftl et al. [30] proposed the scale-shift invariant loss to leverage the training on multi-source data, which can achieve promising generalization on diverse scenes. Yin et al. [54] employ a heterogeneous loss training strategy, which obtains state-of-the-art performance on multiple zero-shot testing datasets. Our method is built upon these robust depth estimation methods on different RGB-D datasets for the generalization and detail recovery ability. We also go one step further to remedy the issue of scale-missing by devising a powerful local scale recovery technique with additional easy-access information.

RGB-D Datasets. Datasets [9, 32, 35, 38] are significant for the advancement of data-driven depth prediction methods. Current datasets can be summarized into two categories according to their quality. Some datasets are captured by RGB-D sensors, which can retrieve accurate metric depth. Make3D [32] is the first outdoor RGB-D dataset constructed for monocular depth prediction study. KITTI and NYU are captured by LIDAR on outdoor streets and Kinect in indoor rooms. Larger-scale RGB-D datasets are also constructed, such as ScanNet [9], Taskonomy [55], DIML [7], and DIODE [38]. These datasets usually contain very limited scenes only.

To compress more diversified scenes, some algorithms try to leverage online images and videos. Chen et al. [2] constructed the largest RGB-D dataset, where the ground-truth depth maps were manually annotated with only one pair of ordinal relations. MegaDepth [22] employs structure from motion to construct the depth supervision on the still and rigid scenes. To include more non-rigid and diverse scenes, Xian et al. [43] and Wang et al. [39] adopted optical flow techniques to build datasets of relative depth. Chen et al. [4] released the diverse OASIS dataset, which contains both ordinal depth annotations and camera intrinsic parameters. Yin et al. [51, 53] propose another large-scale and diverse RGB-D datasets: DiverseDepth.

Depth Completion. Depth completion aims to recover a dense depth map from a very sparse input. Some methods [3, 5, 6, 28, 50] combine the RGB texture information with sparse depth together to solve the problem. Promising results have been obtained on KITTI and NYU benchmarks. Except for these very sparse depth types, commodity-level RGB-D cameras such as Kinect, RealSense, and Tango produce depth images that are semi-dense but missing certain regions. Several methods treat this as a depth inpainting task and leverage smoothness priors [16], background surface extrapolation [27], and surface normals [57]. Our method can be considered as an alternative approach to depth completion but requires much less guided points.

Video-based Depth Estimation. Video-based depth estimation has attracted extensive attentions recently. They are mainly categorized into multi-view stereo based approaches [11, 24, 36] and hybrid methods [19, 25]. The former try to improve the traditional structure-from-motion and multi-view stereo pipeline with some learning-based modules, such as a differentiable depth and pose modules or a depth estimation uncertainty predictor. Such methods are all based on a cost volume that is constructed by warping neighboring frames to a reference viewpoint. Although
promising results have been achieved, they may fail to handle dynamic scenes. By contrast, the hybrid method aims to combine single-view depth estimation and multi-view stereo for achieving geometrically consistent video depth. In this work, through per-frame prediction and alignment with guided points, we can obtain consistent video depth prediction.

3. Our Method

3.1. Metric Depth Recovery Strategy

Current monocular depth estimation [29,30,51,54] methods have achieved promising results on diverse scenes. The problem is that their predicted depth is scale-shift-invariant, termed affine-invariant depth/inverse depth [51, 53]. To recover the metric depth, it should be scaled and shifted, i.e., \( d^* = ds + \mu \), where \( d \), \( s \), and \( \mu \) are the predicted affine-invariant depth, scale, and shift respectively. Current methods propose to obtain the scale and shift through a global least-squares fitting method using some ground-truth depth:

\[
\min_{\beta} \sum_{i=1}^{n} [y_i - \beta x_i^T]^2, \quad \beta = [s, \mu] \in \mathbb{R}^{1 \times 2}, \quad x_i = [d_i, 1] \in \mathbb{R}^{1 \times 2}
\]

\[
\hat{\beta} = (X^T X)^{-1} X^T y
\]

where \( y \) is the ground-truth metric depth, \( X \) is the homogeneous representation of the predicted depth \( d \). The optimized scale and shift are \( \hat{\beta} \).

The problem is that such a globally scaling and shifting method cannot diminish spatially heterogeneous errors, which always follows a rather simple pattern. For example, we visualize the pixel-wise absolute error map between ground truth and the predicted depth with the recovered scale and shift, see Fig. 1(a). We observe that such a globally recovering method cannot remove the spatial error. The left part shows higher error than that of the right part. Motivated by this observation, we propose to leverage a local recovering method. Guided by very sparse ground truth points, we can use simple regression models, i.e., *locally weighted linear regression (LWLR)*, to fit these error maps. Thus, we propose an effective strategy to quantify and fix these low-rank spatial errors which are common in depth estimation.

**Locally Weighted Linear Regression.** We propose to employ a modified locally weighted regression method, which can assess the spatial heterogeneity in the estimated relationships between the independent and dependent variables. The original method is illustrated as follows.

\[
\min_{\beta_{u,v}} \sum_{i=1}^{m} [y_i - \beta_{u,v} x_{i}^T]^2 \cdot w_{i,u,v}, \quad \beta_{u,v} = [s_{u,v}, \mu_{u,v}] \in \mathbb{R}^{1 \times 2}, \quad x_i = [d_i, 1] \in \mathbb{R}^{1 \times 2}
\]

\[
\hat{\beta}_{u,v} = (X^T W_{u,v} X)^{-1} X^T W_{u,v} y
\]

Here, \( y \) represents the ground-truth metric depth of sparse guided points (we use around 25~100 points in practice), \( X \) is the homogeneous representation of the predicted depth \( d \) at these guided points, \( \beta_{u,v} \) is the scale and shift at the image location \((u, v)\). \( W_{u,v} \) is a weight matrix. Such a weight matrix gives the most weight to the data points closest to the point of estimation and the least weight to the data points that are the furthest away. The use of the weights is based on the idea that points near each other in the explanatory variable space are more likely to be related to each other in a simple way than points that are further apart. In our implementation, we employ a Gaussian kernel function.

\[
w_{i,u,v} = \frac{1}{\sqrt{2\pi b^2}} \exp\left(-\frac{d_{i,u,v}^2}{2b^2}\right)
\]

where \( b \) is the bandwidth of the Gaussian kernel, and \( d_{i,u,v} \)
is the Euclidean distance between the guided point \((u_i, v_i)\) and target point \((u, v)\).

Figure 2. Distribution of recovered scales with locally weighted linear regression methods. (a) Scale distribution of original algorithm in Eq. (2), which contains negative values and spreads widely. (b) Scale map of our proposed algorithm in Eq. (4), which is positive and reasonable.

Such obtained scale map and shift map can yield much more accurate metric depth than the previous global methods. However, we observe that some values of the scale map can be fitted to negative due to the shift-invariant characteristic of monocular depth and flexibility of the weighted linear regression, which inverses the distribution of depth prediction and lacks reasonableness. The distribution of scale is shown in Fig. 2(a). Since the bias is not centered and the solution space is not bounded, results are wildly distributed with no physical meanings and far from the real scale and shift. Therefore, we proposed to align monocular depth with sparse ground truth first, and restrict the solution to be simple by adding an \(\ell_2\) regularization on the shift.

\[
\begin{align*}
\min_{\beta_{u,v}} & \sum_{i=1}^{m}[y_i - \beta_{u,v} x_i^T]^2 w_{i,u,v} + \lambda[\beta_{u,v}[1]]^2, \\
\beta_{u,v} &= [s_{u,v}, \mu_{u,v}] \in \mathbb{R}^{1 \times 2}, x_i \in \mathbb{R}^{1 \times 2}, \\
\hat{\beta}_{u,v} &= (X^T W_{u,v} X + A)^{-1} X^T W_{u,v} y, \\
A &= \begin{bmatrix} \lambda & 0 \\ 0 & 0 \end{bmatrix}
\end{align*}
\]

where, \(\beta_{u,v}[1]\) is the shift value at point \((u, v)\). With the regularizer of shift, the location-related scale map is encouraged to be positive and reasonable, as shown in Fig. 2(b). Finally, with the optimized scale and shift at location \((u, v)\), we can obtain its metric depth \(d^*_{u,v} = s_{u,v} \cdot d + \mu_{u,v}\).

With our proposed local recovery strategy, we only need a very sparse set of ground-truth depth values (around 25~100 points) to recover the metric depth map by fitting a location-related scale map and a shift map. Fig. 1 compares the global least-square fitting and our proposed weighted linear regression results. Owing to optimized pixel-wise scale map (Fig. 1(c)) and shift map (Fig. 1(d)), the overall loss is reduced significantly (Fig. 1(b)). Note that the predicted affine-invariant depths are the same for two methods.

Importantly, the recovered metric depth with our method is highly linear correlated to the ground truth (see Fig. 1(e) and Fig. 1(f)).

| Dataset             | # images | Scene   | Quality   |
|---------------------|----------|---------|-----------|
| Taskonomy [56]      | 4.5M     | Indoor  | High-quality |
| ApolloScape [40]    | 114K     | Outdoor | High-quality |
| Hypersim [31]       | 298K     | Indoor  | High-quality |
| GraspNet [12]       | 82K      | Indoor  | High-quality |
| Tartanair [41]      | 289K     | Synthetic | High-quality |
| UASOL [1]           | 162K     | Outdoor | Mid-quality |
| DrivingStereo [48]  | 182K     | Outdoor | Mid-quality |
| DIML [8]            | 121K     | Outdoor | Mid-quality |
| HoloPix50k [17]     | 99K      | Indoor  | Low-quality |
| KeystoneDepth [26]  | 74K      | In the wild | Low-quality |
| WSVD [39]           | 117K     | In the wild | Low-quality |
| HRWSI [45]          | 18K      | Outdoor | Low-quality |
| MegaDepth [22]      | 79K      | Outdoor | Low-quality |
| DiverseDepth [53]   | 90K      | In the wild | Low-quality |
| **Total**           | **6.3M** |         |            |

Table 1. Diverse training data used in our experiment.

3.2. Boosting Monocular Depth and Monocular Video Depth Estimation

In this work, following LeReS [54], we collect over \(6.3\) Million data to train a strong and robust monocular depth estimation model. With only around one hundred points, we can obtain very accurate metric depth. Comparing to existing depth completion methods [5, 28], which take sparse points as input for learning, our method is a simple and effective learning-free post process. It can be easily plugged to any monocular depth estimation and completion methods to boost performance.

Furthermore, our recovery strategy and strong model can be combined to solve the video depth estimation problem. Current video depth estimation methods mainly try to leverage inter-frame consistency or multi-view geometry constraints. We observe that performing per-frame prediction and the scale-shift alignment with very sparse guided points, we can obtain accurate and consistent metric video depth prediction.

**Consistency Metric for Video Depth Estimation.** We propose the average distortion distance (ADD) error to evaluate the consistency of predicted video depths. The predicted depths of consecutive frames are unprojected to 3D space and establish their correspondence with known camera poses, intrinsic parameters and ground-truth depth. The average distortion distance (ADD) measures the average


| Method          | Backbone  | KITTI AbsRel↓ | NYU AbsRel↓ | ScanNet AbsRel↓ | ETH3D AbsRel↓ | DIODE AbsRel↓ |
|-----------------|-----------|--------------|-------------|----------------|--------------|--------------|
| OASIS [44]      | ResNet50  | 31.7         | 43.7        | 21.9           | 66.8         | 19.8         | 67.9         | 29.2         | 59.5         | 48.4         | 53.4         |
| MegaDepth [23]  | ResNet50  | 20.1         | 63.3        | 19.4           | 71.4         | 19.0         | 71.2         | 26.0         | 64.3         | 39.1         | 61.5         |
| Xian et al. [44] | ResNet50  | 27.0         | 52.9        | 16.6           | 77.2         | 18.9         | 71.4         | 26.1         | 61.9         | 35.8         | 63.8         |
| WSVD [39]       | ResNet50  | 24.4         | 60.2        | 22.6           | 65.0         | 18.9         | 71.4         | 26.1         | 61.9         | 35.8         | 63.8         |
| Chen et al. [3] | ResNet50  | 32.7         | 51.2        | 16.6           | 77.3         | 16.5         | 76.7         | 23.7         | 67.2         | 37.9         | 66.0         |
| DiverseDepth   | ResNet50  | 19.0         | 70.4        | 11.7           | 87.5         | 10.8         | 88.2         | 22.8         | 69.4         | 37.6         | 63.1         |
| LeRes [54]      | ResNet101 | 14.8         | 78.6        | 8.6            | 92.1         | 9.5          | 91.2         | 9.7          | 90.3         | 21.6         | 80.8         |
| MiDaS-large     | ResNet101 | 13.4         | 81.9        | 10.2           | 90.0         | 9.8          | 90.9         | 10.1         | 90.5         | 19.0         | 76.1         |
| DPT-large       | ViT-Large | 10.0         | 90.1        | 9.8            | 90.3         | 7.8          | 93.8         | 7.8          | 94.6         | 18.2         | 75.8         |
| Ours(global)    | ResNet50  | 10.9         | 88.5        | 8.2            | 92.6         | 8.9          | 92.0         | 8.4          | 92.1         | 22.0         | 80.1         |
| Ours(local)     | ResNet50  | 5.7 (−48%)   | 95.4 (−43%) | 4.7 (−52%)     | 96.9 (−52%)   | 5.0 (−40%)   | 97.4 (−52%)   | 5.0 (−40%)   | 96.6 (−40%)   | 16.5 (−25%)   | 85.2         |

Table 2. Quantitative comparison of monocular depth estimation with state-of-the-art methods on five unseen datasets. ‘global’ and ‘local’ represents global and our proposed local metric depth recovery strategy separately. For global strategy, our ResNet50 [15] model outperforms other ResNet50 and ResNeXt101 [47] models on four test datasets. With our proposed local recovery and 100 sparse ground truth, our ResNet50 model achieves significant improvement and outperforms state-of-the-art DPT [29] with the ViT-large [10] backbone.

| Method       | KITTI AbsRel↓ | NYU AbsRel↓ | ScanNet AbsRel↓ | ETH3D AbsRel↓ | DIODE AbsRel↓ |
|--------------|---------------|-------------|-----------------|---------------|---------------|
| LeRes [54]   | before 14.8   | after 8.0   | (−46%)          | before 9.5    | after 4.4     | (−54%)          | before 9.7    | after 5.6     | (−42%)          | before 21.6    | after 16.2   | (−25%)          |
| MiDaS-large  | before 13.4   | after 6.2   | (−54%)          | before 10.2   | after 5.1     | (−50%)          | before 9.8    | after 4.3     | (−56%)          | before 10.1    | after 4.9     | (−52%)          | before 19.0    | after 14.5    | (−24%)          |
| DPT-large    | before 10.0   | after 5.2   | (−48%)          | before 9.8    | after 5.0     | (−49%)          | before 7.8    | after 3.8     | (−51%)          | before 7.8      | after 4.2     | (−54%)          | before 18.2    | after 14.3    | (−21%)          |
| NLSNP [28]   | before -      | after -     | -               | before -       | after -       | -               | before -       | after -       | -               | before -       | after -       | -               |
| VNL [52]     | before -      | after -     | -               | before -       | after -       | -               | before -       | after -       | -               | before -       | after -       | -               |
| Monodepth2 [14] | before 8.1   | after 6.1   | (−25%)          | before -       | after -       | -               | before -       | after -       | -               | before -       | after -       | -               |

Table 3. Boosting various monocular depth estimation with our local recovery method. We compare the accuracy without (see ‘before’ columns) and with (see ‘after’ columns) our recovery methods. We can see the performance of all these monocular depth estimation (such as VNL [52], Monodepth2 [14], DPT [29], and so on) and depth completion (NLSNP [28]) methods are boosted significantly.

Distance of paired 3D points:

$$ADD = \frac{1}{n} \sum_{j=1}^{n} ||c_{ij} - c_{2j}||_{\theta}$$

$$c_{ij} = R_i K_i^{-1} d(p_{ij}) \bar{p}_{ij} + T_i, \quad i, 1, 2$$

Here, $c_{ij}$ is the 3D coordinates of paired point $j$ in frame $i$, $p_{ij}$ is the 2D pixel location, $\bar{p}_{ij}$ is its homogeneous representation, $d(p_{ij})$ is the prediction depth of $p_{ij}$, and $K_i$, $R_i$, $T_i$ represents the intrinsic parameters, rotation, and translation of frame $i$, respectively.

4. Experiments

Training Datasets. To train a robust monocular depth estimation model, 6.3 million diverse RGB-D pairs are processed and trained following the previous work LeRes [54], and the composition of datasets is listed in Table 1.

Implementation Details. Following [51, 54], we balance high-quality, middle-quality, and low-quality data in each batch to ensure that they accounts for almost the same ratio in each batch. For example, each data accounts for $N/3$ if the batch size is set to $N$ during training. Multiple data augmentation techniques are used, such as random flipping, color transformations, image blur and so on. We randomly crop the image by $448 \times 448$ for training. ResNet50 [15] with ImageNet pretrained weight is adopted in our experiments. We use SGD with momentum, starting with a learning rate of 0.04. It is decayed with 0.1 for 4 times. The batch size is set to 128.

Evaluation Details. We evaluate the absolute mean relative error (AbsRel error) and the percentage of pixels with

$$\delta_1 = \max(\frac{d_{pred}}{d_{gt}}, \frac{d_{gt}}{d_{pred}}) < 1.25$$

on 5 zero-shot datasets including KITTI [13], NYU [34], ScanNet [9], ETH3D [33] and DIODE [38]. The consistency evaluation experiments of video depth estimation and 3D scene reconstruction are performed on 5 NYU videos. Besides the AbsRel error metric and $\delta_1$, the average distortion distance (ADD) proposed in Sec. 3.2 is also evaluated to show the video depth consistency.

4.1. Monocular Depth Estimation

Comparison with State-of-the-art Methods. In this experiment, we compare with state-of-the-art robust monoc-
ular depth estimation methods on five zero-shot datasets. Their scale and shift are recovered with a globally least-square fitting method. Note that we use their released weight for evaluation, and the results are shown in Table 2. Our method with the ResNet50 backbone, recovering the scale and shift with the proposed locally weighted linear regression method (‘Ours (local)’), can outperform all previous methods by a large margin over all zero-shot testing datasets. Note that our training data is comparable to that of DPT and DPT used a much stronger transformer backbone (ViT-large [10]). Furthermore, our locally scale-shift recovering method is better than previous global method (‘Ours (global)’) significantly.

Effectiveness of Locally Weighted Linear Regression and Decoupling of Monocular Depth Error. To demonstrate our proposed locally weighed linear regression can boost various monocular depth estimation methods, we enforce it on multiple different methods: 1) learning affine-invariant depth methods, e.g., LeReS [54], MiDaS [30], and DPT [29]; 2) learning metric depth on a specific dataset (VNL [52]); 3) learning scale-invariant depth with unsupervised methods (MonoDepth2 [14]); 4) depth completion method (NLSPN [28]). Results are shown in Table 3. We uniformly sample 100 guided points to do the local recovery. All their performances are boosted significantly (see the ‘after’ columns). Critically, the NLSPN method has input such 100 sampled points for completion, but our method can still further boost its performance. Note that we used their released weights and code for this experiment.

Besides improving performance, local recovery strategy is also performed to decouple monocular depth error between ground truth and global aligned prediction into coarse misalignment error and detail missing error. Compared with the error of global recovery, the alleviated error in percentage brought by local recovery represents the coarse mis-

| Amount | Distribution | Noise | b | NYU | AbsRel | δ1 |
|--------|--------------|------|---|-----|--------|----|
| 10×10  | Grid         | 0%   | 50| 4.8 | 96.4   |
| 5×5    | Grid         | 0%   | 50| 5.8 | 94.7   |
| 20×20  | Grid         | 0%   | 50| 4.6 | 96.7   |
| 10×10  | Grid         | 0%   | 25| 4.7 | 96.0   |
| 10×10  | Grid         | 10%  | 50| 5.8 | 95.5   |
| 10×10  | Grid         | 20%  | 50| 5.5 | 96.2   |
| 100    | Uniform (whole image) | 0% | 50| 4.3 | 97.0   |
| 100    | Uniform (half image) | 0% | 50| 11.3| 87.6   |

Table 5. Ablation study for parameters of our proposed local recovery strategy. Amount, distribution and error correspond to the number, the distribution and the perturbation percentage of sampled ground-truth. Parameter b represents the bandwidth of the Gaussian kernel function.

Ablation Study for Training Data. In this experiment, we aim to study the relations between the data volume and performance improvement. We gradually aggregate more data for training, and evaluate the performance on 5 zero-shot datasets. Note that 3 different quality data sources are increased in balance, and the results are illustrated in Table 4. We can observe that when the data size increases from 42k to 900K (around by 20 times), the performance is boosted significantly. However, when further increasing by 7 times, the accuracy can only be improved slightly. We conjecture that such a large-scale data has fully exploited the capacity of the model (ResNet50 backbone).

Furthermore, we also conduct local recovery here to decouple the error into coarse misalignment error and detail missing error, as mentioned in the last paragraph. As shown in Table 4, the percentage of coarse misalignment error remains nearly constant, which shows the model can study the detail information and the global structure simultaneously. Fig. 3 shows an overall decrease of mean average error and standard deviation for the scale and shift map. It represents the enhancement of ability to generate accurate global structure without the help of local recovery.

Ablation Study for the Locally Weighted Linear Regression Method. The performance of our proposed local recovery strategy may be affected by the amount of sparse points, the sparsity distribution, noises from sparse points, and the bandwidth b. Their effects for the depth accuracy is explored and shown in Table 5. All experiments are conducted on the NYU dataset.

From the ablation study, we can see that simple 5 × 5 ground truth depth can be leveraged to recover metric depth and improve the accuracy. The more ground truth points we use, the better performance we can achieve. It is also worth mentioning that our method is robust to a uniform sample strategy and noises of ground truth, but the overly concentrated sampling strategy should be avoided in practice.
Figure 3. Analysis for the distribution of scale map and shift map. The ideal values of scale and shift are 1 and 0 separately, with which model can align metric depth well without local recovery. The overall decrease of mean average error and standard deviation shows the progressive enhancement of depth prediction.

Figure 4. Qualitative comparison of depth estimation with state-of-the-art methods including LeReS [54], MiDaS [30], and DPT [29].

As for the parameter, Gaussian kernel bandwidth $b$, it represents the effect of distance to the weight matrix. Experimentally, we suggest to simply set parameter bandwidth to the value $l/n$, where $l$ is the width of the RGB image and $n$ is the number of sampled ground-truth points of one side. More precisely, if we sample $10 \times 10$ ground-truth points for an $500 \times 500$ image, the parameter bandwidth can be set to 50. For images with extreme aspect ratio like KITTI, $l$ can be a compromise between them.
Figure 5. Qualitative comparison of 3D scene reconstruction from video. We compare with three representative methods: single image depth estimation method LeReS [54] aligned with ground truth depth, robust depth estimation method RCVD [19] with iterations of consistency optimization between frames, and depth completion method NLSPN [28] with sparse ground truth. 15% outliers of NLSPN are filtered out during visualization due to the noise of depth prediction. As the figure shows, our method reconstructs better 3D shape in both accuracy and consistency (see arrows).

Table 6. Quantitative comparison of monocular video depth estimation with single image depth estimation, consistent video depth estimation and depth completion methods. ‘ADD’ is our video consistency evaluation metric proposed in Sec. 3.2. Our pipeline of 3D scene reconstruction from video achieves state-of-the-art performance on 5 NYU videos.

4.2. Video Depth Estimation and 3D Reconstruction

Video Consistency. With our well-trained model and the locally scale and shift recovery method, we can achieve high-quality video metric depth through per-frame prediction. To evaluate the consistency and accuracy of video depths, we collect 5 NYU videos and compare with the single image 3D reconstruction method (LeReS [54]), a state-of-the-art depth completion method (NLSPN [28]), and the latest robust consistent video depth estimation method (RCVD [19]). Note that only NLSPN is trained on NYU and can predict metric depth. Our method and NLSPN use the same sparse guided points (100 points). For LeReS and RCVD, we align their predictions with the ground truth metric depth globally before evaluation. The AbsRel error, $\delta_1$, and our proposed average distortion distance error (‘ADD’, see Sec. 3.2) are employed for evaluation.

Comparisons are shown in Table 6. First, we compare with the depth completion method, NLSPN [28], which also uses the sparse guided points to obtain metric information. The main difference is that their model should be trained on the test set and lacks generalization in the wild. By contrast, we can achieve better performance and generalize well to zero-shot datasets due to the robust depth prior. RCVD [19] aims to solve the consistency problem for video depth prediction, and LeReS [54] performs well in the wild. Compared with them, our method achieves state-of-the-art in accuracy and consistency.

Furthermore, we conduct the qualitative comparison on NYU and KITTI. Results are shown in Fig. 5. We do the per-frame depth prediction and un-project them to the same 3D coordinate space. Depth completion method NLSPN cannot recover high-quality details. The consistency
of RCVD is much better on NYU, but the 3D structure is not accurate, see the walls. LeReS achieves excellent detail prediction but lack consistency between frames for misalignment caused by global recovery strategy. With our local recovery strategy, our method can reconstruct a better 3D point cloud than others.

5. Limitations and Discussion

We observe some limitations of our method. First, the improvement brought by local recovery strategy still relies on sparse ground truth depth, which limit the application. Second, we propose to decouple the inaccuracy and alleviate the coarse misalignment with our strategy, but ignore the detail missing inaccuracy. For future work, sparse ground truth can be replaced by some traditional geometric algorithm. High-frequency inaccuracy can be reduced by post-processing algorithms of enhancing detail information.

6. Conclusion

In this paper, we have developed a modified locally weighted linear regression strategy to significantly improve the accuracy and consistency of depth estimation, with robustness to both the amount and randomly-generated noises of the ground truth. Extensive experiments show that the proposed strategy owns significant generalization ability to monocular depth estimation and also potential practical values.

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Appendix

We provide more information here.

A. Datasets for Training

During training, we collect over 6.3 million data to improve the robustness of our monocular depth estimation model. These datasets are separated into high-quality, mid-quality and mid-stereo following [54], and are processed as follows:

For low-quality web-stereo data, such as WSVD [39] and HoloPix50k [17], we follow [39, 43] to employ an optical flow method, RAFT [37], to obtain the relative depth. Frames are sampled every 3 seconds for WSVD videos. For the high-quality Taskonomy [56], we employ the least-square fitting to recover also possible instance planes, which are used in the pair-wise normal regression loss [54]. Furthermore, we employ the latest semantic segmentation method, Segformer [46], to separate the sky regions in all data and set them with the largest depth value during training.

B. Analysis of the Amount of Ground-truth Points

Figure S1. Comparison of local and global recovery strategy of predicted depth, uniform and grid sample strategy of GT points during recovering monocular metric depth. With our proposed local recovery, the performance of monocular depth estimation improves significantly with the increase of GT points. Also, the grid sampling strategy outperforms the uniform one, which can reduce the requirements for GT points.

![Table S1](image)

| GT Points | Local-Uniform | Global-Uniform | Local-Grid | Global-Grid |
|-----------|---------------|----------------|------------|-------------|
| 1         | 73.84         | 73.84          | 74.43      | 74.43       |
| 2         | 72.1          | 27.1           | -          | -           |
| 3         | 14.73         | 14.78          | -          | -           |
| 4         | 12.77         | 13.15          | 9.33       | 10.23       |
| 5         | 10.73         | 11.23          | -          | -           |
| 6         | 9.56          | 10.2           | -          | -           |
| 7         | 9.13          | 10.07          | -          | -           |
| 8         | 8.85          | 9.85           | -          | -           |
| 9         | 8.49          | 9.74           | 7.1        | 9.18        |
| 10        | 7.09          | 9.11           | 5.9        | 8.76        |
| 25        | 6.17          | 8.68           | 5.38       | 8.62        |
| 36        | 5.74          | 8.56           | 5.12       | 8.52        |
| 49        | 5.4           | 8.36           | 5.06       | 8.58        |
| 64        | 5.2           | 8.33           | 4.92       | 8.49        |
| 81        | 5.06          | 8.4            | 4.79       | 8.48        |
| 100       | 4.9           | 8.41           | 4.68       | 8.46        |
| 144       | 4.78          | 8.34           | 4.55       | 8.43        |
| 196       | 4.62          | 8.26           | 4.47       | 8.42        |
| 256       | 4.57          | 8.28           | 4.4        | 8.33        |
| 324       | 4.49          | 8.24           | 4.35       | 8.35        |
| 400       | 4.42          | 8.21           | 4.3        | 8.34        |
| 900       | 4.23          | 8.24           | 4.13       | 8.27        |

Table S1. Analysis for the amount of ground-truth (GT) points during recovering monocular metric depth. ‘Global’ and ‘Local’ represent global recovery and local recovery strategy separately. ‘Grid’ and ‘Uniform’ stand for sampling from grid and uniformly. The AbsRel error decrease faster with our proposed local recovery strategy with the increase of GT points.

C. Analysis for Depth Error Map and Efficiency of Local Recovery Strategy

In Fig. S3, we visualize the error map between ground truth depth and predicted depth aligned through global recovery (see ‘Global Error’ row) and local recovery (see ‘Local Error’ row) separately. The local recovery strategy can generate an oppositely distributed scale map (see ‘Scale Map’ row) and a fine-tune shift map (see ‘Shift Map’ row) to alleviate the coarse misalignment of predicted depth. Our proposed local recovery strategy also improves the linear relation of prediction-GT pairs (compare ‘Local Curve’ row with ‘Global Curve’ row).

D. Illustration of the 3D Point Cloud

We illustrate some examples of 3D point cloud unprojected from our proposed per-frame monocular video depth estimation pipeline in Fig. S2. The video depth is predicted by monocular depth estimation module and aligns consistent metric depth between frames by sparse GT points.
Figure S2. Illustration of the reconstructed 3D point cloud. The columns show the input RGB videos and point cloud un-projected from left, right, top view separately.
Figure S3. Analysis for depth error map, scale map and prediction-GT curve of monocular depth estimation. Our proposed local recovery strategy can generate an oppositely distributed scale map compared with error map of global recovery, which can alleviate the coarse misalignment of predicted depth and improve the linear relation of prediction-GT pairs.