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ABSTRACT

Depth estimation aims to predict dense depth maps. In autonomous driving scenes, sparsity of annotations makes the task challenging. Supervised models produce concave objects due to insufficient structural information. They overfit to valid pixels and fail to restore spatial structures. Self-supervised methods are proposed for the problem. Their robustness is limited by pose estimation, leading to erroneous results in natural scenes. In this paper, we propose a supervised framework termed Diffusion-Augmented Depth Prediction (DADP). We leverage the structural characteristics of diffusion model to enforce depth structures of depth models in a plug-and-play manner. An object-guided integrality loss is also proposed to further enhance regional structure integrality by fetching objective information. We evaluate DADP on three driving benchmarks and achieve significant improvements in depth structures and robustness. Our work provides a new perspective on depth estimation with sparse annotations in autonomous driving scenes.

CCS CONCEPTS

• Computing methodologies → Scene understanding.

KEYWORDS

depth prediction, diffusion model, autonomous driving

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Figure 1: Comparisons with supervised [35, 36, 53] or selfsupervised [14, 51, 55] methods on nuScenes [6]. The Xaxis represents δ_1 . The Y-axis represents RMSE. Our DADP achieves state-of-the-art performance and improvements with different depth predictors in a plug-and-play manner.

1 INTRODUCTION

Depth prediction aims to predict dense depth maps, whether in supervised or self-supervised paradigm. However, sparse depth annotations in driving scenes pose an obstacle for the task.

LiDAR is one primary acquisition equipment for driving datasets but only generates sparse annotations. NuScenes [6], DDAD [16], and KITTI [13] only have 0.24%, 1.85%, and 15.8% pixels with valid ground truth respectively. In contrast, depth models are supposed to predict dense results with both accurate details and integral spatial structures. Due to insufficient structural information, supervised [35, 36, 53] or self-supervised [14, 51, 55] methods produce failure predictions with concave objects, erroneous outcomes, or noticeable artifacts on autonomous driving scenarios [6, 16].

Supervised methods [35, 36, 48, 53, 57] employ various loss functions [10, 26, 28, 36, 47, 53] to measure the discrepancy between output depth and ground truth. However, models fail to acquire sufficient structural information from sparse annotations of driving scenes. They overfit to pixels with valid ground truth and cannot preserve regional structures (*i.e.*, complete shape of objects) and holistic structures. As shown in Fig. 5, supervised models [35, 36, 53] trained on nuScenes [6] produce concave areas on

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objects. They even exhibit holistically wrong spatial structures with striped artifacts, overfitting to horizontally-distributed annotations from LiDAR. As proved in Sec. 4.2, these defects cannot be solved by common techniques for overfitting such as data augmentations or weight decay [32]. Previous supervised models and loss [35, 36, 53] show limitations on sparse depth annotations of driving scenes.

To enhance spatial structures, recent works [14, 17, 19, 51, 55] explore self-supervised manner on driving scenes [6, 16]. Surround-Depth [51] employs pseudo labels from Structure-from-Motion [40] to pretrain their model. They utilize pose estimation and photometric loss [12] between six cameras to restore depth structures. MCDP [55] conducts multi-camera prediction by projections between different views. However, self-supervised methods rely on pose estimation [14], which is inaccurate in natural scenes and limits the robustness of those methods. As shown in Fig. 6, they produce erroneous results on night or rainy scenes. Besides, deploying multiple cameras on driving cars [51] is inflexible and costly.

To overcome these challenges, we propose a novel supervised framework with sparse annotations termed Diffusion-Augmented Depth Prediction (DADP). Our method does not rely on pose estimation and multiple cameras, achieving better robustness than self-supervised methods [14, 17, 19, 51, 55], especially for challenging night or rainy scenes. DADP consists of a noise predictor and a depth predictor. The depth predictor can be different supervised single-image depth models. The core task is to enhance depth structures. Recent diffusion models in other tasks [1, 25, 37, 52] showcases favorable structural properties, which can span coherent parts of objects as shown in Fig. 4. To acquire integral spatial structures, we introduce the noise predictor similar to diffusion models [8, 23] but in a plug-and-play manner. To be specific, we add Gaussian noise to input images. The noise predictor is trained to predict noise components. We fuse the structure-aware features from noise predictor and the detail-aware features from depth predictors, predicting depth maps with both accurate details and complete structures. The noise predictor can be adopted to off-the-shelf depth predictors in a plug-and-play manner. Besides, to further improve regional structure integrality of objects, we design our object-guided integrality loss that fetches objective structural information.

Experiments are conducted on prevailing driving benchmarks nuScenes [6], DDAD [16], and KITTI [13]. DADP effectively alleviates concave objects and artifacts produced by supervised depth predictors [35, 36, 53]. Compared with self-supervised methods [14, 51, 55], quantitative and qualitative results prove the robustness of our DADP on challenging driving scenes with glare, reflections, rain, or weak-textured areas. As shown in Fig. 1, DADP achieves stateof-the-art performance over previous supervised or self-supervised methods. We also adopt three different depth predictors [35, 36, 53] and demonstrate the effectiveness of our plug-and-play paradigm. The main contributions can be summarized as follows:

- We present a plug-and-play framework with sparse depth annotations termed Diffusion-Augmented Depth Prediction (DADP).
- We propose a noise predictor to enforce depth structures in different depth predictors, utilizing structural properties of diffusion models to remedy sparse annotations in autonomous driving.
- We design object-guided integrality loss to further enhance the completeness of objects with objective structural information.

2 RELATED WORK

Depth Datasets for Autonomous Driving. Most driving depth datasets are captured by LiDAR and suffer from sparsity of ground truth. NuScenes [6] is a large-scale dataset captured by a sensor suite (with six cameras, one LiDAR, five RADAR, GPS, and IMU). It contains 1,000 driving scenes in Boston and Singapore. NuScenes [6] is quite challenging for its low density of depth annotations (0.24%) and its complex in-the-wild scenes. DDAD [16] is an urban driving dataset captured by six synchronized cameras and a high-resolution Luminar-H2 LiDAR. It is designed for long-range depth estimation in diverse urban scenes. The annotation density in DDAD [16] is 1.85%. KITTI [13] is another widely-used autonomous driving dataset with annotation density of 15.8%. It contains 61 outdoor scenes with binocular views from a driving car.

Supervised Depth Estimation. In recent years, supervised depth models [4, 27, 36, 49, 53] have significantly improved the depth accuracy. DPT [35] utilizes the vision transformer [9] for depth prediction and semantic segmentation. The structure-guided ranking loss is proposed by Xian *et al.* [53] with a novel sampling strategy for learning from pseudo-depth data. Midas [36] adopts a multi-objective learning strategy and trains depth models on mixing datasets. PackNet-SAN [15] improve spatial structural integrity by jointly learning depth estimation and depth completion.

Under sparse annotations of driving scenes, those supervised models produce incomplete objects and artifacts. In this work, we present our novel supervised framework DADP. Thanks to the structure information from our noise predictor and the structure guidance from our object-guided integrality loss, the above-mentioned defects can be solved in a plug-and-play manner.

Self-supervised Depth Estimation. To enhance depth structures on driving scenes [6, 16], prior arts [17, 19, 20, 51, 55] seek for the self-supervised paradigm. They jointly optimize a pose module and a depth module by photometric loss [12]. Monodepth2 [14] introduces the multi-scale sampling strategy and minimum re-projection loss to deal with obscuring situations. The cross-view transformer is proposed by SurroundDepth [51] to improve self-supervised methods on surrounding views. MCDP [55] iteratively optimizes depth results with neighboring cameras for consistent structures.

However, self-supervised methods [17, 19, 20, 51, 55] rely on pose estimation, which is unreliable and significantly limits their robustness. In contrast, our DADP achieves better robustness without pose estimation and multiple cameras.

Diffusion Models. Sohl-Dickstein *et al.* [42] first design the diffusion probabilistic model, learning to invert the diffusion process. Ho *et al.* [23] propose the DDPM framework to generate high-quality image samples. By learning the process of denoising, the diffusion model can generate images with both vivid details and reasonable structures. A series of improvements on model structures [8, 34] and sampling strategies [2, 39, 43] lead to the great success of diffusion models in generation tasks. They can synthesize realistic effects with reasonable spatial relations and structures according to prior conditions [8, 24, 37, 38]. Those results indicate that diffusion models acquire a strong capability of structural representations.

In our work, we leverage the structural information embedded in the diffusion models to enhance regional and holistic spatial structures for depth estimation on sparse driving scenes [6, 13, 16].



Diffusion-Augmented Depth Prediction (DADP)

Figure 2: Overview of DADP framework. DADP contains a noise predictor and a depth predictor. The depth predictor can be different single-image depth models. The noise predictor is an Unet [8] to predict the noise component of diffusion step $q(x_t|x_0)$. We fuse structure-aware features from noise predictor and detail-aware features of depth predictor to enhance depth structures with sparse annotations on driving scenes. We also propose object-guided integrality loss to improve objective structural integrity. Our loss guides abnormal regions M_i^{ab} with incorrect depth variation to normal depth range in different objects. Better viewed when zoomed in.

3 PROPOSED METHOD

3.1 Overview

Fig. 2 showcases the technical pipeline of our Diffusion-Augmented Depth Prediction (DADP) framework. On autonomous driving scenarios only with sparse annotations [6, 16], the key problem is to enforce regional and holistic spatial structures without the unreliable pose estimation in prior arts [14, 19, 20, 51, 55]. DADP contains two main components: a depth predictor and a noise predictor. The depth predictor can be different single-image depth models such as Xian et al. [53], Midas [36], and DPT [35]. The noise predictor is a Unet [8, 34] to predict noise components of the diffusion process. The noise predictor and diffusion models [23] are trained to predict noise components and generate noise-free images from the noisy ones. In this way, the noise predictor acquires favorable structural properties as demonstrated in Sec. 4.2. We adopt the noise predictor to restore depth structures. Specifically, we fuse the structure-aware features from the noise predictor and the detail-aware features from the depth predictor by feature fusion modules (FFM) [30, 31]. Ultimately, depth predictors can restore both accurate details and integral spatial structures.

We conduct a two-stage training procedure. First, we train the noise predictor on RGB images with the subtask of unconditional image generation as DDPM [8, 23, 34]. Once the noise predictor is trained, its parameters are fixed. It can be directly adopted to the training of different depth predictors in a plug-and-play manner. The next step is the supervised training for depth predictors. To further improve the regional structural integrality, we design our object-guided integrality loss which fetches the spatial structural information of different objects. To be specific, we utilize a state-of-the-art panoptic segmentation model [7] to segment different objects. We focus on abnormal regions within each object, *i.e.*,

concave areas with incorrect depth variation. Our loss guides those abnormal regions to integral depth structures.

During inference, along with the noise predictor, depth predictors predict depth maps with regionally and holistically complete spatial structures, removing the incomplete objects, concave areas, and artifacts produced by previous supervised depth predictors [35, 36, 53] on sparse driving scenes [6, 16]. Without relying on pose estimation, our DADP achieves better robustness than self-supervised frameworks [14, 51, 55] on challenging scenarios.

3.2 Noise Predictor

Preliminaries. Diffusion models [3, 8, 23, 43] are latent variable models for generative tasks, which are trained to denoise Gaussianblurred images and reverse the diffusion process. If we denote a noise-free input RGB image as $x_0 \in \mathbb{R}^{h \times w \times 3}$ and the maximum diffusion step as *T*, the diffusion process of diffusion step $t \in \{0, 1, \dots, T\}$ can be formulated as follows:

$$q(x_t \mid x_0) \coloneqq \mathcal{N}\left(x_t; \sqrt{\bar{\alpha}_t} x_0, (1 - \bar{\alpha}_t) I\right),$$

$$x_t = \sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon, \quad \epsilon \sim \mathcal{N}(0, 1),$$
(1)

where $\alpha_t := 1 - \beta_t$ and $\bar{\alpha}_t := \prod_{s=0}^t \alpha_s$. β is the noise variance schedule as DDPM [23]. $x_t \in \mathbb{R}^{h \times w \times 3}$ represents the resulting high-noise image of diffusion step *t*. N denotes Gaussian noise.

As for the denoising process, a noise predictor $\epsilon_{\theta}(x_t, t)$ is trained to reverse the diffusion process and restore the noise-free x_0 . Each denoising step is approximated by a Gaussian distribution:

$$p_{\theta}\left(x_{t-1} \mid x_{t}\right) \coloneqq \mathcal{N}\left(x_{t-1}; \mu_{\theta}\left(x_{t}, t\right), \Sigma_{\theta}\left(x_{t}, t\right)\right) . \tag{2}$$

The noise predictor $\epsilon_{\theta}(x_t, t)$ predicts the noise component of step *t* and obtains the mean value $\mu_{\theta}(x_t, t)$ of above-mentioned Gaussian distribution by linear combination of x_t . The covariance predictor $\Sigma_{\theta}(x_t, t)$ can be fixed [23] or learned [8]. By iterating the denoising process, the noise-free image x_0 can be recovered.

Depth Structure Augmentation. We adopt an Unet as the noise predictor with multi-resolution attention [8] and BigGAN up-/down-sampling [5]. It is trained on RGB images with mean square error (MSE) between the predicted and actual noise components. In Sec. 4.2, we prove that the noise predictor acquires a strong ability of structural representations by denoising RGB images. After the training of noise predictor, we freeze its parameters and utilize its structure-aware features to augment depth structures in a plug-and-play manner. See supplementary for details of the noise predictor.

As shown in Fig. 2, we fuse the structure-aware features from noise predictor and the detail-aware features from depth predictor by feature fusion modules (FFM) [30, 31]. The CNN decoder of the depth predictor gradually improves spatial resolutions and predicts depth results. Specifically, if we denote the block indexes of the noise predictor as *b*, we leverage structure-aware features $\{t = 50, b = 12\}, \{t = 100, b = 8\}, \text{ and } \{t = 150, b = 5, 6, 7\}$ from the noise predictor. Resolutions of the structure-aware features are adjusted to 1/2, 1/4, and 1/8 of input resolution respectively.

The ultimate step is to train depth predictors [35, 36, 53]. Directly training depth predictors on highly sparse driving scenes [6, 16] will produce incomplete objects, concave areas, and artifacts by previous supervised training procedures and loss functions [10, 36, 53]. With

the structure information from noise predictor, our DADP can remove those defects and predict depth maps with regionally and holistically integral spatial structures. The noise predictor can be adapted to different depth predictors [35, 36, 53] in a plug-and-play manner. As for the supervision between predicted depth and ground truth, we adopt the commonly-applied affinity invariant loss [36]. More importantly, to further improve the regional integrality of objects, we propose to use the objective structural information as guidance, which will be illustrated in the next section.

3.3 Object-Guided Integrality Loss

With the structural information from the noise predictor described above, our DADP is capable to restore spatial structures from sparse depth annotations of autonomous driving scenarios. To further improve the integrity of different objects, we propose the objectguided integrality loss as regional structural guidance.

The design of our object-guided integrality loss is based on a simple prior that the depth values inside a certain object should be continuous and smooth. Our loss focuses on the areas with abnormal depth variation inside each object and guides them back to normal depth values. Thus, we need to extract each object region from the input image. In our implementation, we utilize the state-of-the-art Mask2Former [7] to perform panoptic segmentation and extract the object mask of each instance. Here, we denote the object masks as \mathbf{M}_i^{obj} , $i \in \{1, 2, \dots, K\}$, where K represents the number of objects in the input image.

Specifically, given the noise-free input image \mathbf{x}_0 , we denote the predicted and ground truth depth as $\hat{\mathbf{d}}$ and $\hat{\mathbf{d}}^*$, which are aligned to zero translation and unit scale as MiDaS [36] to deal with varied scale and shift of different depth predictors [35, 36, 53]. For each object \mathbf{M}_i^{obj} , we segment the corresponding region of predicted depth, denoted by $\hat{\mathbf{d}}_i$. The operation can be easily achieved by dot product between object mask \mathbf{M}_i^{obj} and predicted depth $\hat{\mathbf{d}}$. Similarly, We obtain the list $\hat{\mathbf{d}}_i^*$ of valid ground truth values within the object.

The next step is to find the areas with abnormal depth variation inside each object. We consider the normal depth range in object \mathbf{M}_{i}^{obj} with upper bound \mathbf{U}_{i} and lower bound \mathbf{L}_{i} as follows:

$$\begin{aligned} \mathbf{U}_{i} &= (1+\alpha) * max(max(\hat{\mathbf{d}}_{i}^{*}), median(\hat{\mathbf{d}}_{i})) ,\\ \mathbf{L}_{i} &= (1-\alpha) * min(min(\hat{\mathbf{d}}_{i}^{*}), median(\hat{\mathbf{d}}_{i})) , \end{aligned} \tag{3}$$

where α is the tolerance factor. To be mentioned, for some small objects with no valid ground truth, *i.e.*, $\hat{\mathbf{d}}_i^*$ is empty, we use the median value of $\hat{\mathbf{d}}_i$ with tolerance factor α for \mathbf{U}_i and \mathbf{L}_i . In contrast, when pixels with valid ground truth exist in the object, the maximum and minimum value of $\hat{\mathbf{d}}_i^*$ will be adopted.

Our loss encourages depth values inside the object to be continuous and smooth. Pixels with depth values out of the normal depth range will be divided into abnormal areas. However, the segmentation model [7] cannot handle some complex occlusions, *e.g.*, sky regions with tree branches. Pixels that actually do not belong to the certain object should be removed from \mathbf{M}_i^{obj} . For this problem, we conduct k-means clustering [21] on the input image \mathbf{x}_0 within the object \mathbf{M}_i^{obj} . Pixels with the lowest 20% cosine similarity to their corresponding clustering centers are removed. If we denote those

pixels to be removed as the mask M_i^{occ} , the final abnormal region M_i^{ab} as shown in Fig. 2 is presented as follows:

$$\mathbf{M}_i^{ab} = (\hat{\mathbf{d}}_i > \mathbf{U}_i) \cup (\hat{\mathbf{d}}_i < \mathbf{L}_i) - \mathbf{M}_i^{occ} .$$

$$\tag{4}$$

Finally, the abnormal depth values should be guided to the normal depth range. If we denote the pixels within \mathbf{M}_{i}^{ab} as p, our object-guided integrality loss can be formulated as:

$$\mathcal{L}_{obj}\left(\hat{\mathbf{d}},\mathbf{U},\mathbf{L}\right) = \frac{1}{K} \sum_{i=1}^{K} \sum_{p=1}^{N_i} \min\left(\left|\hat{\mathbf{d}}_i^{(p)} - \mathbf{U}_i\right|, \left|\hat{\mathbf{d}}_i^{(p)} - \mathbf{L}_i\right|\right), \quad (5)$$

where N_i is the number of pixels in \mathbf{M}_i^{ab} . See supplementary for more visual results of the masks in our loss.

3.4 Implementation Details

Noise Predictor. For our noise predictor, the maximum diffusion step *T* is set to 1000. we resize images to 256×256 and adopt a batch size of 8 for training. We use the Adam optimizer with learning rate 1e - 4.

The mean square error (MSE) between the predicted and actual noise components is used for supervision. The parameters of our noise predictor are fixed after the first stage of training.

Depth Predictor. To prove our plug-and-play manner, we adopt Xian *et al.* [53], DPT-hybrid [35] and Midas-v2 [36] as depth predictors in our experiments. Xian *et al.* [53] is trained from scratch, while DPT [35] and Midas [36] are fine-tuned on nuScenes [6] and DDAD [16] datasets from their pretrained checkpoints.

For the training of depth predictors, following prior arts [15, 51, 55], we utilize the training resolution of 640×352 on nuSceness dataset [6] and 640×384 on DDAD dataset [16]. We train depth predictors for 5 epochs on the nuScenes [6] and 20 epochs on DDAD [16] with a batch size of 16. The initial learning rate is set to 5e - 5 and decreases by 1e - 5 for every five epochs. For KITTI [13] dataset, we follow the same standard training procedure as BTS [29]. Except for our object-guided integrality loss, we adopt the commonly-applied affinity invariant loss [35, 36] \mathcal{L}_{af} between predicted depth and ground truth. See supplementary for more details. The overall loss \mathcal{L} can be expressed as:

$$\mathcal{L} = \mathcal{L}_{af} + \lambda \mathcal{L}_{obj} , \qquad (6)$$

where the coefficient λ is 0.1. We set the tolerance factor $\alpha = 0.1$.

4 EXPERIMENTS

In this section, we evaluate our Diffusion-Augmented Depth Prediction (DADP) framework on prevailing autonomous driving datasets nuScenes [6], DDAD [16], and KITTI [13]. We first briefly describe the evaluation protocol and datasets in Sec. 4.1. Some experimental results are shown to further expound on our motivations in Sec. 4.2. The quantitative and qualitative comparisons with state-of-the-art approaches are shown in Sec. 4.3. We also conduct ablation studies and prove the effectiveness of our design in Sec. 4.4.

4.1 Evaluation Protocol and Datasets

Evaluation Protocol. For supervised depth models, we compare our DADP with Xian *et al.* [53], Midas [36], and DPT [35] as different depth predictors, which demonstrates our effective plug-and-play manner. Those models [35, 36, 53] are trained on nuScenes [6]



Figure 3: Visual results with data augmentations and weight decay [32]. We train Midas [36] on nuScenes dataset [6] with several data augmentations (Aug) and L_2 regularization (Reg) for weight decay. We highlight regions with prominent difference in dashed rectangular. The incomplete objects, concave areas, and artifacts cannot be solved by those common techniques for overfitting. Better viewed when zoomed in.

and DDAD [16] with their original training pipeline. On DDAD [16] dataset, we also compare our approach with previous state-of-theart supervised framework PackNet-SAN [15]. Following PackNet-SAN [15], we evaluate supervised methods [15, 35, 36, 53] on four views of DDAD [16], due to self-occlusion in the other two views.

Self-supervised methods [14, 17, 19, 51, 55] with pose estimation of multiple views are prevailing on autonomous driving datasets [6, 16]. Consequently, we also compare our DADP with them, even though the quantitative comparisons between supervised and selfsupervised methods might be unfair. We mainly compare and demonstrate the robustness of our DADP especially in challenging driving scenes with glare and reflections at night, rainy scenes, or weak-textured areas. Our approach does not utilize the unreliable camera poses. Following previous state-of-the-art self-supervised MCDP [55] on DDAD [16] dataset, we compare with self-supervised approaches [15, 35, 36, 53] on six views of DDAD [16].

Datasets. We mainly compare those supervised or self-supervised methods on nuScenes [6] and DDAD [16] datasets. To demonstrate the robustness of our framework, we further evaluate different approaches with daytime and nighttime scenes on nuScenes [6] dataset. For sufficient comparisons and evaluations, we also compare with those methods on KITTI [13] dataset. See supplementary for the experimental results on KITTI [13] dataset.

Evaluation Metrics. We evaluate the performance of different approaches with the commonly-applied depth metrics including *Abs Rel*, *Sq Rel*, *RMSE*, and δ_i (*i* = 1, 2, 3).

4.2 Motivation Review

Dominant autonomous driving depth datasets NuScenes [6] and DDAD [16] only have 0.24% and 1.85% pixels with depth ground truth. Directly training fully supervised depth estimation models [35, 36, 53] on those highly sparse driving scenes produces concave regions, incomplete objects, or even some artifacts in predicted depth maps. Due to the lack of structural information in the sparse annotations, models could overfit to pixels with valid ground truth and fail to establish regional and holistic spatial structures. MM '23, October 29-November 3, 2023, Ottawa, ON, Canada



Figure 4: Visual comparisons of features. We visualize feature maps from CNN encoders [22, 54] and the structure-aware features in our noise predictor by k-means [21] clustering (k=5). Our noise predictor shows better representations of spatial structures, which can span coherent parts of objects.

Experimental results prove that those defects cannot be solved by common techniques for overfitting such as data augmentations or weight decay [32]. We train Midas [36] with weight decay [32] and several data augmentations on nuScenes [6] dataset. Specifically, we adopt random cropping, horizontal flipping, and color jittering as data augmentations (Aug). We also apply L_2 regularization (Reg) for weight decay. As shown in Fig. 3, the above-mentioned defects still remain with data augmentations and weight decay [32]. The incomplete objects and concave areas cannot be improved without sufficient structural information and guidance.

Previous supervised learning approaches [15, 35, 36, 53] cannot handle the sparsity problem for autonomous driving. They do not conduct experiments on nuScenes [6] dataset while only PackNet-SAN [15] shows results on DDAD [16] dataset. To establish complete spatial structures on those sparse driving scenes [6, 16], most previous works [14, 17, 19, 51, 55] seek for the self-supervised learning manner with pose estimation in multiple views. However, camera poses are inaccurate and unreliable on many challenging scenes and limit the robustness of those self-supervised approaches [14, 17, 19, 51, 55]. As shown in Fig. 6, previous Monodepth2 [14] and SurroundDepth [51] produce erroneous predictions on night or rainy scenes.

We are devoted to solving this dilemma. We prefer not to rely on the pose estimation and self-supervised manner considering their limited robustness on natural scenes. The key problem is to enforce integral spatial structures under the condition of highly sparse depth annotations. An intuitive idea is to fuse spatial features extracted from RGB images by convolutional encoders [22, 54]. Specifically, we replace the noise predictor with widely-used CNN encoders [22, 54] and fuse the extracted features into the depth predictor. However, concave objects and artifacts are not settled. More quantitative and visual depth comparisons can be found in our supplementary. We visualize the feature maps of the CNN encoders [22, 54] by k-means clustering [21]. As shown in Fig. 4,

Method	NuScenes				DDAD							
	Abs Rel↓	Sq Rel↓	RMSE↓	$\delta_1 \uparrow$	$\delta_2\uparrow$	$\delta_3 \uparrow$	Abs Rel↓	Sq Rel↓	RMSE↓	$\delta_1 \uparrow$	$\delta_2 \uparrow$	$\delta_3 \uparrow$
Xian <i>et al.</i> [53]	0.147	1.375	6.266	0.799	0.913	0.957	0.150	3.281	12.784	0.810	0.914	0.954
PackNet [18]	-	-	-	-	-	-	0.125	2.158	11.245	0.836	0.929	0.962
MiDaS [36]	0.122	1.106	5.485	0.844	0.933	0.964	0.137	2.904	11.870	0.836	0.929	0.964
DPT [35]	0.121	1.074	5.315	0.851	0.934	0.965	0.134	2.630	11.913	0.837	0.930	0.964
PackNet-SAN [15]	-	-	-	_	-	-	0.119	1.931	10.852	0.850	0.936	0.977
Ours(Xian et al.)	0.131	1.141	5.952	0.824	0.924	0.963	0.138	2.297	11.150	0.838	0.934	0.967
Ours(MiDaS)	0.117	1.084	5.370	0.856	0.938	0.967	0.122	2.227	10.406	0.866	0.945	0.970
Ours(DPT)	0.112	1.010	5.181	0.867	0.941	0.968	0.118	2.140	10.130	0.870	0.946	0.972

Table 1: Comparisons with supervised depth estimation approaches on nuScenes [6] and DDAD [16]. The first five rows are results of previous state-of-the-art supervised models. We show our results with different depth predictors in the last three rows, which demonstrate the effectiveness of our plug-and-play manner. Following PackNet-SAN [15], we evaluate supervised approaches on four views of DDAD [16]. Best performance is in boldface. Second best is underlined.

Method	NuScenes				DDAD								
	Abs Rel↓	Sq Rel↓	RMSE↓	$\delta_1 \uparrow$	$\delta_2\uparrow$	$\delta_3 \uparrow$	_	Abs Rel↓	Sq Rel↓	RMSE↓	$\delta_1 \uparrow$	$\delta_2 \uparrow$	$\delta_3 \uparrow$
Monodepth2 [14] (-M)	0.287	3.349	7.184	0.641	0.845	0.925		0.217	3.641	12.962	0.699	0.877	0.939
PackNet-SfM [17] (-M)	0.309	2.891	7.994	0.547	0.796	0.899		0.234	3.802	13.253	0.672	0.860	0.931
FSM [19]	0.334	2.845	7.786	0.508	0.761	0.894		0.229	4.589	13.520	0.677	0.867	0.936
TransDSSL [20]	-	-	-	-	_	-		0.151	3.591	14.350	_	_	_
SurroundDepth [51]	0.245	3.067	6.835	0.719	0.878	0.935		0.200	3.392	12.270	0.740	0.894	0.947
MCDP [55]	0.237	3.030	6.822	0.719	-	-		0.193	3.111	12.264	0.811	-	-
Ours(Xian et al.)	0.131	1.141	5.952	0.824	0.924	0.963		0.146	2.352	10.778	0.826	0.927	0.962
Ours(MiDaS)	0.117	1.084	5.370	0.856	0.938	0.967		0.132	2.312	10.087	0.856	0.938	0.966
Ours(DPT)	0.112	1.010	5.181	0.867	0.941	0.968		0.130	<u>2.338</u>	9.994	0.860	0.939	0.966

Table 2: Comparisons with self-supervised depth estimation approaches on nuScenes [6] and DDAD [16] datasets. The first six rows are results of previous state-of-the-art self-supervised models. Our results with different depth predictors are in the last three rows. Best results are highlighted in bold. Second best is underlined. (-M) indicates occlusion masking [51] in DDAD [16].

detailed RGB information rather than spatial structures are presented by CNNs [22, 54]. For better spatial structures, motivated by recent diffusion models [3, 8, 33, 43, 44], we propose our DADP with the noise predictor. The noise predictor is trained to denoise and generate noise-free images from noisy ones. This subtask can enforce better representations of spatial structures in the structureaware features as shown in Fig. 4. With the structural information from the noise predictor, our DADP predicts depth results with integral regional and holistic structures, significantly alleviating the incomplete objects and artifacts.

Besides, to further guide integral regional structures of objects, we design the object-guided integrality loss. Our loss focuses on the areas with abnormal depth variation inside a certain object and guides the depth values to normal depth range. Overall, our DADP and object-guided integrality loss significantly improve depth structures on sparse autonomous driving scenarios [6, 16] and obtain better robustness without using pose estimation of multiple views.

4.3 Comparisons with state-of-the-art results

Comparisons with supervised methods. We compare our DADP with previous supervised depth estimation approaches [15, 18, 35,

36, 53]. We present quantitative comparisons in Table 1 and qualitative results in Fig. 5. For PackNet [18] and PackNet-SAN [15], we report their official depth metrics on DDAD dataset [16]. For Xian *et al.* [53], Midas [36], and DPT [35], we train their models on nuScenes and DDAD datasets [6, 16] with their original training pipeline. In Fig. 5, we can observe that previous supervised frameworks [35, 36, 53] produce obvious concave areas, incomplete objects, or even artifacts. With the structural information from the noise predictor, our DADP effectively releases those defects and achieves state-of-the-art performance as shown in Table 1.

Besides, we also fit the three different supervised depth models [35, 36, 53] as depth predictors into our DADP framework. Our approach can effectively deal with different depth predictors in a plug-and-play manner. With Xian *et al.* [53], Midas [36], and DPT [35] as depth predictors on DDAD [16] dataset, our DADP shows 2.8%, 3.0%, and 3.3% improvements of δ_1 respectively. The quantitative metrics cannot fully reflect our improvements due to the sparse ground truth. Both the depth metrics and visualizations demonstrate the effectiveness of our plug-and-play manner.

Comparisons with self-supervised frameworks. Due to the challenging sparse annotations for autonomous driving, most previous depth estimation methods on nuScenes [6] and DDAD [16]



Figure 5: Visual comparisons with supervised depth prediction methods on nuScenes dataset [6]. We adopt supervised models [35, 36, 53] as different depth predictors in our DADP framework. Our approach effectively releases concave areas, incomplete objects, and artifacts produced by depth predictors. Regions with prominent difference are highlighted in dashed rectangular.



Figure 6: Visual comparisons with self-supervised methods [14, 51]. Without relying on pose estimation, our DADP shows significantly better robustness in challenging scenes with glare and reflections at night, rainy scenes, or weaktextured areas. Better viewed when zoomed in.

datasets are in the self-supervised paradigm with pose estimation. We compare our DADP with previous self-supervised frameworks [14, 17, 19, 20, 51, 55] in Table 2 and Fig. 6. We know that it might be unfair to compare supervised approaches with selfsupervised methods. However, it is meaningful to explore supervised learning frameworks on sparse driving scenes. The robustness of self-supervised methods is limited due to the unreliable camera poses. Accurate pose estimation itself is a challenging task especially on in-the-wild images with glare and reflections at night, rainy Table 3: Comparisons on daytime and nighttime scenes of nuScenes dataset [6]. We evaluate both supervised and selfsupervised approaches [14, 35, 36, 51]. Our approach shows better robustness on both daytime and nighttime scenarios.

Method	Abs Rel \downarrow	Sq Rel↓	RMSE↓	$\delta_1 \uparrow$	δ_2	$\delta_3\uparrow$			
Daytime Scenes									
Monodepth2 [14]	0.263	2.772	7.061	0.660	0.854	0.928			
SurroundDepth [51]	0.236	3.002	6.754	0.738	0.889	0.940			
MiDaS [36]	0.118	1.176	5.212	0.859	0.937	0.967			
DPT [35]	0.115	1.049	5.269	0.863	0.938	0.967			
Ours(MiDaS)	0.111	1.049	5.292	0.871	0.943	0.969			
Ours(DPT)	0.106	0.984	5.120	0.879	0.946	0.970			
	Night	time Sce	nes						
Monodepth2 [14]	0.585	18.715	12.119	0.484	0.732	0.851			
SurroundDepth [51]	0.330	3.638	7.563	0.542	0.784	0.890			
MiDaS [36]	0.198	1.699	6.197	0.697	0.871	0.940			
DPT [35]	0.177	1.297	5.727	0.743	0.891	0.948			
Ours(MiDaS)	0.182	1.397	6.068	0.722	0.884	0.948			
Ours(DPT)	0.166	1.243	5.731	0.757	0.896	0.952			

scenes, or weak-textured areas. Whether compared with supervised or self-supervised methods, our DADP shows better qualitative and quantitative performance. Compared with self-supervised approaches, our DADP does not utilize camera poses and achieves better robustness on challenging driving scenes as shown in Fig. 6. **Robustness on Challenging Driving Scenes.** To further demonstrate our robustness on challenging driving scenes, we evaluate previous supervised and self-supervised approaches [14, 35, 36, 51] with daytime and nighttime scenes respectively on nuScenes



Figure 7: Qualitative ablation of DADP framework. The noise predictor enforces integral structures and removes stripped artifacts in the depth predictor [53]. The object-guided integrality loss further improves regional structural completeness of objects. Better viewed when zoomed in.

Table 4: Ablation of our noise predictor and object-guided integrality loss with Xian *et al.* [53] as the depth predictor.

Method	Abs Rel↓	Sq Rel↓	RMSE↓	$\delta_1 \uparrow$	$\delta_2 \uparrow$	$\delta_3\uparrow$
Xian <i>et al.</i> [53]	0.183	1.375	6.266	0.799	0.913	0.957
Ours $(w/o\mathcal{L}_{obj})$	0.140	1.292	6.001	0.820	0.921	0.960
Ours (w/\mathcal{L}_{obj})	0.132	1.141	5.951	0.824	0.925	0.963

dataset [6]. The results are shown in Table 3. Compared with stateof-the-art self-supervised SurroundDepth [51] with pose estimation, our DADP showcases 21% δ_1 improvements in the challenging nighttime scenes. Compared with the supervised models, our method also outperforms DPT [35] by 4.2% in *Sq Rel* for nighttime. Whether compared with previous supervised or self-supervised approaches, our framework shows better robustness on challenging autonomous driving scenes with highly sparse depth annotations.

4.4 Ablation Studies

Effectiveness of DADP Framework. We ablate the noise predictor and our object-guided integrality loss to demonstrate the effectiveness of our design. In this experiment, we adopt Xian *et al.* [53] as the depth predictor on nuScenes dataset [6]. Quantitative results are shown in Table 4. Thanks to the structural information from the noise predictor, our DADP achieves 2.1% improvement on δ_1 compared with the depth predictor. By adding our object-guided integrality loss for supervision, the depth accuracy further improves. To be mentioned, the quantitative metrics with sparse ground truth cannot fully reflect our improvements in depth structures.

Visual comparisons are shown in Fig. 7. The noise predictor enforces spatial structures and removes the stripped artifacts in the depth predictor [53]. Meanwhile, our object-guided integrality loss can further improve the regional object completeness, for example, removing the concave areas on the window of the car. These structural improvements could not be presented by the depth metrics. Those concave areas might have few pixels with valid ground truth.



Figure 8: Ablation of annotation density on DDAD dataset. DDAD [16] dataset has 1.85% pixels with valid ground truth. We train our DADP with Midas [36] as the depth predictor using different portions of the valid pixels. Our DADP framework shows strong robustness on high annotation sparsity.

Table 5: Ablation of diffusion steps on nuScenes [6] dataset.

Diffusion Steps	Abs Rel \downarrow	$\operatorname{Sq}\operatorname{Rel}{\downarrow}$	RMSE↓	$\delta_1 \uparrow$	$\delta_2 \uparrow$	δ_3
(0, 50, 100)	0.135	1.207	5.964	0.820	0.923	0.962
(100, 150, 200)	0.137	1.214	6.010	0.817	0.922	0.962
(50, 100, 150)	0.132	1.141	5.951	0.824	0.925	0.963

Density of Depth Annotations. Different autonomous driving datasets [6, 13, 16] possess different annotation density. To demonstrate the robustness of our framework on high sparsity, we randomly sample several portions of valid pixels for training on DDAD dataset [16]. As shown in Fig. 8, with lower annotation density, our DADP shows stronger robustness than the depth predictor [36]. When the portion decreases to the extremely low 10%, i.e., only with 0.185% pixels with valid annotations, our DADP still showcases 3.2% improvements on δ_1 over Midas [36] as the depth predictor. Diffusion Steps. In this experiment, we ablate different diffusion steps on nuScenes [6] dataset. The experimental results are shown in Table 5. With larger diffusion steps, features become more abstract and structural while remaining less details. Structure-aware features of the noise predictor should achieve a balance of structural and detailed information. As a consequence, we choose the best-performing diffusion steps of (50, 100, 150) in our experiments.

5 CONCLUSION

Previous supervised depth methods lead to concave areas and artifacts on sparse driving scenes. In this paper, we propose a supervised framework termed Diffusion-Augmented Depth Prediction (DADP). With the structural information from our noise predictor and structural guidance from our object-guided integrality loss, DADP effectively alleviates those defects in a plug-and-play manner. Compared with the prevailing self-supervised methods, our DADP is more robust on challenging scenes without relying on pose estimation. Further analysis shows the efficacy of our design and proves that DADP can adapt to varied annotation density. Our work shows strong effectiveness in the field of autonomous driving.

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A MORE DETAILS ON DADP FRAMEWORK

A.1 The Noise Predictor

We adopt Unet as the noise predictor with multi-resolution attention [8] and BigGAN residual blocks [5]. Here we specify the details.

As shown in Fig. 9, the noise predictor downsamples the input noisy image to 1/32 of the original resolution. For each resolution, two Resblocks [22] are used for feature extraction. Linear layers are used in these blocks to embed the diffusion step *t*. We utilize multihead self-attention [45] on resolutions of 32×32 , 16×16 , 8×8 to improve the representation ability. Besides, the simple up-sampling and down-sampling between different resolutions are replaced by the residual blocks in BigGAN [5], which can reduce information loss and improve the generation quality.



Figure 9: Architecture of the noise predictor. Some resolutions are omitted for simplicity. Blue arrows indicate the residual blocks in BigGAN [5] for up-/down-sampling. Two Resblocks [22] are used for each resolution.

A.2 Object-guided Integrality Loss

Here we explain different masks in the object-guided integrality loss. We visualize M^{obj} , M^{ab} , and M^{occ} for interpretation in Fig. 10. The indices *i*, *j*, and *k* represent different objects in the input image. M^{ab} can effectively mark the abnormal depth areas in the certain object M^{obj} . For the regions with complex occlusions or segmentation errors, such as the region beneath the M_k^{obj} in the third row, we also exclude them as the M_k^{occ} by k-means clustering [21].



Figure 10: Masks in object-guided integrality loss. The yellow areas in the rgb images represent the object mask M^{obj} obtained by segmentation model [7]. The green areas M^{ab} in the third column indicate the regions with abnormal depth variations. The blue area M^{occ} represents the excluded pixels with segmentation errors by k-means clustering [21]. The indices i, j, k denote specific objects in the three images.

A.3 Affinity Invariant Loss

For the training of the depth predictor [35, 36, 53], we also use the affinity invariant loss [35, 36] in addition to the proposed objectguided integrality loss. Here we briefly present the details. If we denote the original predicted depth and ground truth as **d** and d^* , the scale $s(\mathbf{d})$ and shift $t(\mathbf{d})$ of prediction **d** can be obtained as:

$$t(\mathbf{d}) = median(\mathbf{d}), s(\mathbf{d}) = \frac{1}{M} \sum_{i=1}^{M} |\mathbf{d}_i - t(\mathbf{d}_i)|, \qquad (7)$$

where *M* denotes the number of pixels. $t(\mathbf{d}^*)$ and $s(\mathbf{d}^*)$ can also be calculated similarly. Then the prediction **d** and the ground truth \mathbf{d}^* are aligned to zero translation and unit scale:

$$\hat{\mathbf{d}} = \frac{\mathbf{d} - t(\mathbf{d})}{s(\mathbf{d})}, \hat{\mathbf{d}}^* = \frac{\mathbf{d}^* - t(\mathbf{d}^*)}{s(\mathbf{d}^*)}$$
 (8)

 $\hat{\mathbf{d}}$ and $\hat{\mathbf{d}}^*$ represent the aligned prediction and ground truth respectively. The affinity invariant loss \mathcal{L}_{af} can be formulated as:

$$\mathcal{L}_{af}\left(\hat{\mathbf{d}},\hat{\mathbf{d}}^{*}\right) = \frac{1}{2M} \sum_{i=1}^{M} \left|\hat{\mathbf{d}}_{i} - \hat{\mathbf{d}}_{i}^{*}\right|,\tag{9}$$

B DEPTH ESTIMATION METRICS

We adopt the commonly-applied depth metrics defined as follows:

- Absolute relative error (Abs Rel): $\frac{1}{|M|} \sum_{d \in M} |d d^*| / d^*$;
- Square relative error (Sq Rel): $\frac{1}{|M|} \sum_{d \in M} ||d d^*||^2 / d^*$
- Root mean square error (RMSE): $\sqrt{\frac{1}{|M|}\sum_{d\in M} \|d d^*\|^2}$;
- Accuracy with threshold t: Percentage of d_i such that

$$max(\frac{d_i}{d_i^*}, \frac{d_i^*}{d_i}) = \delta < t \in \left[1.25, 1.25^2, 1.25^3\right]$$

where *M* denotes numbers of pixels with valid depth annotation, d_i and d_i^* are estimated and ground truth depth of pixel *i* respectively.

C MORE RESULTS FOR MOTIVATION REVIEW.

Data Augmentation and Weight Decay. In Sec. 4.2 of main paper, we illustrate that data augmentations and weight decay (*e.g.*, regularization) cannot solve the incomplete objects, concave areas, and artifacts for overfitting to sparse valid pixels. The related visual comparisons are given in the Fig. 3 of the main paper. Here we provide the corresponding quantitative metrics in Table 6.

We find that data augmentations reduce the depth accuracy for the reason that those augmentations change the data distribution of nuScenes dataset [6]. The random cropping sometimes leads to even sparser depth supervision. Our method improves the depth accuracy and enhances the spatial structural integrity of the predicted depth maps by fusing structure-aware features from the noise predictor. **Features of CNN Encoders.** In Sec. 4.2 of the main paper, the noise predictor is replaced by widely-used CNN encoders [22, 54]. We fuse the extracted features into the depth predictor. The visualization of those features in Fig. 4 of the main paper demonstrates the better representations of spatial structures for our noise predictor. Here we report visual and quantitative results of this experiment.

Table 8: Comparisons with state-of-the-art methods on KITTI dataset [13]. The first five rows contain results of self-supervised methods, while the last seven rows contain supervised approaches. Best performance is in boldface.

Method	Abs Rel↓	Sq Rel↓	RMSE↓	δ_1	$\delta_2 \uparrow$	$\delta_3\uparrow$
Monodepth2 [14]	0.115	0.882	4.701	0.879	0.961	0.982
Packnet-SFM [17]	0.107	0.802	4.538	0.889	0.962	0.981
Shu <i>et al.</i> [41]	0.088	0.712	4.137	0.915	0.965	0.982
PlaneDepth [46]	0.083	0.533	3.919	0.913	0.969	0.985
ManyDepth [50]	0.087	0.685	4.142	0.920	0.968	0.983
DORN [11]	0.072	-	2.626	0.932	0.984	0.994
VNL [56]	0.072	_	3.258	0.938	0.990	0.998
MiDaS [36]	0.069	0.280	3.006	0.949	0.991	0.998
Ours(MiDaS)	0.065	0.253	2.832	0.955	0.992	0.998
BTS [29]	0.059	0.241	2.756	0.956	0.993	0.998
DPT [35]	0.062	0.222	2.573	0.959	0.995	0.999
Ours(DPT)	0.059	0.230	2.661	0.965	0.995	0.999

Table 6: Comparisons of data augmentations (Aug) and weight decay (Reg) on nuScenes dataset [6].

Method	Abs Rel↓	Sq Rel↓	RMSE↓	$\delta_1 \uparrow$	$\delta_2 \uparrow$	δ_3 ↑
Midas [36]	0.122	1.106	5.485	0.844	0.933	0.964
w/ Reg	0.126	1.154	5.709	0.840	0.930	0.963
w/ Aug	0.141	1.334	5.696	0.816	0.917	0.957
w/ Aug&Reg	0.141	1.339	5.705	0.815	0.919	0.958
Ours(MiDaS)	0.117	1.084	5.370	0.856	0.938	0.967

Table 7: Comparisons with features of different CNN encoders on nuScenes [6]. Best performance is in boldface.

Method	Abs Rel↓	Sq Rel↓	RMSE↓	$\delta_1 \uparrow$	$\delta_2 \uparrow$	$\delta_3\uparrow$
Xian <i>et al.</i> [53]	0.183	1.375	6.266	0.799	0.913	0.957
w/ ResNet50	0.142	1.269	6.054	0.808	0.917	0.960
w/ ResNeXt101	0.140	1.277	5.918	0.813	0.920	0.960
w / noise predictor	0.132	1.141	5.951	0.824	0.925	0.963

As shown in Fig. 11 and Table 7, along with the Fig. 4 in the main paper, we showcase the effectiveness of introducing structure-aware features from the noise predictor and diffusion model. The

results demonstrate that the structure-aware features can significantly improve the spatial structural integrality of output depth.



Figure 11: Visual comparisons with CNN encoders [22, 54]. Our DADP effectively augments spatial structural integrality of depth predictions by noise predictor and diffusion model.

D EXPERIMENTS ON KITTI DATASET

In Sec. 4.1 of the main paper, we mentioned that we also train our DADP on KITTI dataset [13] for sufficient comparisons and evaluations, following the train/test split as Eigen *et al.* [10, 29].

Quantitative comparisons in Table 8 show that our DADP improves the depth accuracy than the depth predictors Midas [36] and DPT [35] on KITTI dataset [13].

E MORE QUALITATIVE DEPTH RESULTS

Due to the sparsity of the depth annotations on autonomous driving scenarios [6, 13, 16], the quantitative metrics cannot fully reflect our improvements. Here we show more visual comparisons to demonstrate the effectiveness of our approach, especially for better spatial structural completeness of the predicted depth maps.

The visual results on nuScenes [6], DDAD [16], and KITTI [13] datasets are shown in Fig. 12, Fig. 13, and Fig. 14 respectively. In Fig. 12, we compare our DADP with different depth predictors [35, 36] on nuScenes dataset [6] to demonstrate our plug-and-play manner. Comparisons with state-of-the-art supervised or self-supervised methods on DDAD dataset [16] are shown in Fig. 13. The proposed DADP framework shows significant improvements than the previous state-of-the-art supervised framework PackNet-SAN [15] on DDAD dataset [16]. Visual comparisons with prior arts on KITTI [13] dataset are also shown in Fig. 14 for sufficient evaluations.

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Figure 12: Visual comparisons on nuScenes dataset [6]. we compare our DADP framework with different depth predictors [35, 36] and state-of-the-art approaches [14, 51]. The results demonstrate the effectiveness of our plug-and-play manner.



Figure 13: Visual comparisons on DDAD [16]. We compare our DADP with state-of-the-art self-supervised [14, 51] and supervised [15] approaches. Our method shows significant improvements than previous state-of-the-art supervised PackNet-SAN [15].



Figure 14: Visual comparisons on KITTI [13] dataset. We compare DADP with state-of-the-art supervised [29, 35, 36, 56] approaches.