

STATIC : Surface Temporal Affine for TIme Consistency in Video Monocular Depth Estimation

Sunghun Yang Minhyeok Lee Suhwan Cho Jungho Lee Sangyoun Lee
Yonsei University
{sunghun98, hydragon516, chosuhwan, 2015142131, syleee}@yonsei.ac.kr

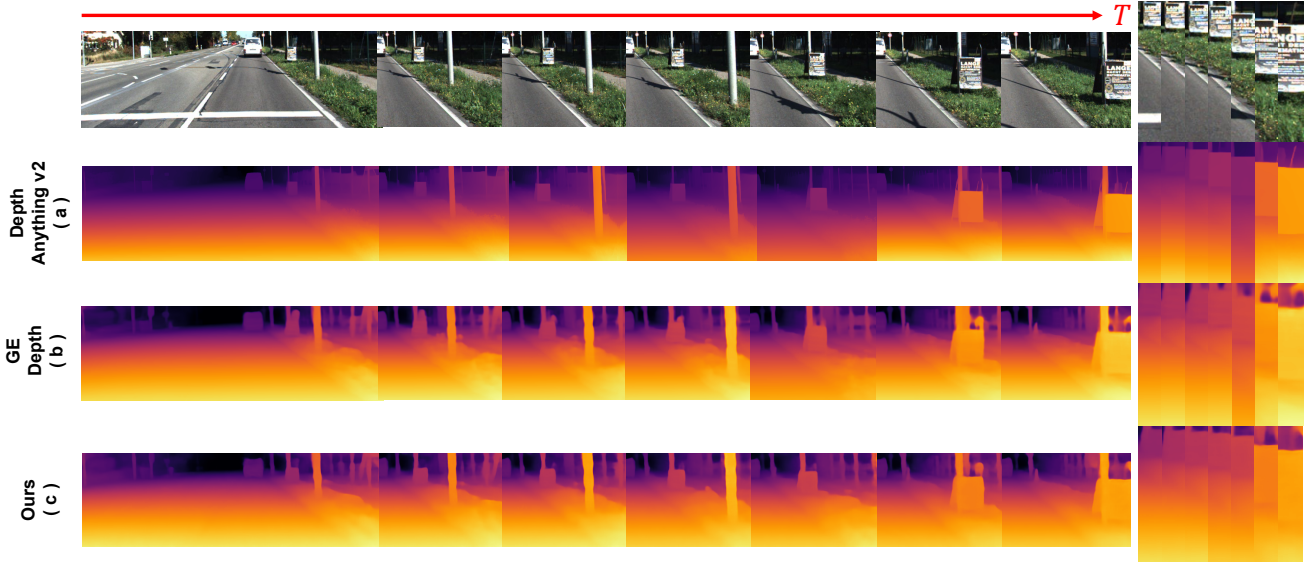


Figure 1. Results of the (a) Depth Anything v2 [48], (b) GEDepth [49] and proposed (c) STATIC from sequential frames. (c) improves ground continuity over the single-frame approach (a) and achieves better temporal consistency in object shape and depth compared to other video depth estimation method (b). For visual comparison, each method is rescaled.

Abstract

Video monocular depth estimation is essential for applications such as autonomous driving, AR/VR, and robotics. Recent transformer-based single-image monocular depth estimation models perform well on single images but struggle with depth consistency across video frames. Traditional methods aim to improve temporal consistency using multi-frame temporal modules or prior information like optical flow and camera parameters. However, these approaches face issues such as high memory use, reduced performance with dynamic or irregular motion, and limited motion understanding. We propose *STATIC*, a novel model that independently learns temporal consistency in static and dynamic area without additional information. A difference mask from surface normals identifies static and dynamic

area by measuring directional variance. For static area, the Masked Static (MS) module enhances temporal consistency by focusing on stable regions. For dynamic area, the Surface Normal Similarity (SNS) module aligns areas and enhances temporal consistency by measuring feature similarity between frames. A final refinement integrates the independently learned static and dynamic area, enabling *STATIC* to achieve temporal consistency across the entire sequence. Our method achieves state-of-the-art video depth estimation on the KITTI and NYUv2 datasets without additional information.

1. Introduction

Depth estimation aims to generate a dense, pixel-level depth map from an RGB image, which is essential in applications

such as autonomous driving, AR/VR, and robotics. Recently, transformer-based monocular depth estimation models [2, 35, 35, 51] have demonstrated superior performance due to their robust generalization abilities, relying on large-scale datasets of paired single-view images and depth maps. In real-world applications like autonomous driving and robotics, depth maps are typically required from consecutive video frames. Monocular depth estimation can process video frames by predicting depth for each frame individually. However, it cannot consider inter-frame depth relationships. As illustrated in Figure 1 (a), per-frame predictions exhibit low inter-frame consistency. To handle these issues, several recent methods address temporal inconsistency by leveraging the global context inferred from multiple frames, enhancing connectivity across the temporal dimension [31, 50, 53]. By using multiple-frame inputs, the model improves inter-frame consistency by learning from diverse scenes. Others use explicit cues like optical flow [8, 47] or camera parameters [3, 40, 49] with high-quality motion estimation to enhance temporal consistency in depth predictions.

However, each previous temporal consistency method faces two major problems. Firstly, many multi-frame methods often focus on broad frame-to-frame changes rather than detailed local motions, making it harder for the model to capture subtle movements. Additionally, processing multiple frames simultaneously leads to inefficiencies and high memory consumption. Secondly, methods using explicit cues poorly perform with dynamic and irregular movements, leading to inaccurate motion information. Moreover, these methods struggle to independently capture the movements of both the foreground and background. This limitation often causes the edges of foreground elements to blur or lose clarity as the background shifts. As shown in Figure 1(b), unclear outlines can be observed for the same object between frames. Additionally, methods using explicit cues can become overly dependent on these additional cues, as mentioned in [22].

To address these issues, we propose a novel video estimation model, Surface Temporal Affine for Time Consistency in Video Monocular Depth Estimation called STATIC. Our model identifies movements between two video frames as the dynamic and static areas without relying on additional motion information. Additionally, STATIC independently learns temporal consistency in both areas, enabling the model to capture various depth changes between frames resulting from different movements in each area. To distinguish the two areas, we generate a difference mask based on surface normals, which represent the scene’s geometric structure. Variations in surface normal between frames indicate geometric transformations or positional shifts, enabling the difference mask to capture these changes through directional variance magnitude.

After separating areas with the difference mask, STATIC learns the static and dynamic area through each module. Since the static area is identical across frames, remaining this area simplifies temporal learning. Therefore, we introduce the Masked Static (MS) Module, which learns the temporal consistency between the first and second frames by remaining only the static area using the difference mask. This enhances continuity in areas such as floors and walls. In contrast, dynamic area with large differences are misaligned and require alignment to achieve temporal consistency. To address this, we introduce the Surface Normal Similarity (SNS) module, which utilizes features to align positions between frames in dynamic area, generating a similarity map that highlights these alignments. Through non-local attention between the query frame and the next frame, we adaptively derive the feature similarity to create a location similarity map. In this process, we concatenate the surface normal and depth features. The surface normal and depth features respectively capture geometric and distance similarity, resulting in a map that highlights spatially and geometrically aligned locations in dynamic area. Thus, the SNS module leverages feature information to identify and learn the movement of identical objects, ensuring spatial and temporal depth consistency despite camera movement. Lastly, a refinement process unifies the independently learned static and dynamic area, enabling STATIC to achieve temporal consistency across the entire sequence.

As shown in Figure 1 (c), the proposed STATIC ensures spatial and temporal consistency across all areas. Our method was evaluated on two widely-used datasets: KITTI Eigen split [13], NYUv2 [39]. STATIC achieves state-of-the-art performance on both without additional information.

Our main contributions are summarized as follows:

- We propose STATIC, a novel video depth estimation model that identifies movements without relying on additional motion information.
- We carefully design a method with the SNS module for dynamic areas and the MS module for static areas to enhance temporal consistency.
- We achieve state-of-the-art performance in the video depth estimation using only image data on the KITTI Eigen split and NYUv2 datasets.

2. Related Work

2.1. Monocular Depth Estimation

Monocular depth estimation, driven by deep learning, predicts depth from a single image as a practical alternative to multi-camera or radar setups. It includes continuous regression for pixel-wise depth [6, 14, 38, 52, 54] and classification-based methods using ordinal regression for depth ordering [4, 9, 24]. Recent integration of Transformer

architectures [35, 48, 51] has further improved accuracy, with encoders capturing long-range dependencies and decoders enhancing feature fusion for refined maps [2]. Despite these advances, monocular depth estimation remains limited by single-frame analysis, missing temporal cues essential for capturing depth changes. Without temporal information, it struggles to adapt to dynamic scenes with moving objects or perspective shifts, often producing unstable predictions when scene depth fluctuates. This instability reduces effectiveness in video applications where consistent depth tracking is crucial.

2.2. Video Depth Estimation

Video depth estimation builds on monocular depth prediction by incorporating temporal consistency and motion cues across frames, enhancing stability and accuracy over time. Unlike single-frame approaches, it captures temporal dependencies to resolve frame-to-frame inconsistencies in dynamic scenes. Recent advancements leverage RNNs [8, 31, 50, 53] and optical flow [12, 16, 41] for improved temporal alignment. RNNs use memory to link depth predictions across frames and enhance stability, while optical flow provides explicit motion cues, aligning depth with object dynamics. Transformers have also been adopted to capture both spatial and temporal dependencies, improving consistency over time. More recently, diffusion models [10, 17, 32], supported by larger datasets, have been explored. However, they mainly enhance data diversity rather than directly tackling the unique challenges of video depth consistency. Despite these advances, challenges remain, particularly the high memory demands and computational costs required to process depth estimation. These limitations highlight the need for further research to achieve more stable and efficient video depth estimation.

2.3. Surface Normal-based Approaches

Previous methods [27, 28] have exploited surface normals to enhance the geometric quality of depth by preserving structures such as corners, boundaries, and planes. Surface normals from local depth gradients remain stable across frames, as gradient directions do not change significantly when large structures are preserved. Even when depth values show low correlation across frames, surface normals remain consistent. However, prior works overlooked this property and focused mainly on sharp edges. Our contribution is to explicitly leverage inter-frame normal consistency in a video-based method, for the first time. Using this property, we compute inter-frame differences by analyzing the variation and dispersion of surface normal directions at each pixel, thereby identifying regions that differ in the subsequent frame. In these regions, our proposed SNS and MS modules enforce consistency, enabling temporally consistent video depth prediction.

3. Method

3.1. Preliminaries

Surface normals, which describe the orientation of surfaces within a scene, are closely related to depth and provide complementary geometric information crucial to maintaining spatial and temporal consistency. This relationship is strong enough that simple operators, like Sobel filters [18], can effectively capture surface normal cues from depth variations, offering a fundamental basis for depth estimation models to understand structural changes across frames. By analyzing directional variations, surface normals assist in identifying changes in scene geometry, allowing depth models to adapt more robustly to transformations without relying on external motion data. This approach enhances stability in dynamic environments, capturing depth details more reliably by leveraging the inherent geometry of the scene.

3.2. Overall Architecture

Figure 2 shows the overall architecture of STATIC. Our model uses only two frames, $I_t \in \mathbb{R}^{3 \times H \times W}$, where $t \in [0, 1]$, as input. I_t is passed through an encoder to obtain the encoder feature. These features are shared by both the surface normal decoder and the depth embedder. The depth embedder processes these features to produce the depth context feature $Z_t^d \in \mathbb{R}^{C^d \times \frac{H}{8} \times \frac{W}{8}}$. Additionally, the encoder feature is passed through a simple surface normal decoder. This decoder generates both the surface normal image $N_t \in \mathbb{R}^{3 \times \frac{H}{8} \times \frac{W}{8}}$ and the surface normal features $Z_t^n \in \mathbb{R}^{C^n \times \frac{H}{8} \times \frac{W}{8}}$, which is a multi-scale normal decoder feature. N_t is utilized to generate a difference mask, which serves to separate regions of structural change. STATIC obtains temporal consistency by employing both the Masked Static (MS) module and the Surface Normal Similarity (SNS) module. The MS module takes depth features and a difference mask as inputs. It applies masking to each frame’s depth feature to generate temporal consistency information for the static area. Additionally, the SNS module takes depth features, surface normal features, and a difference mask as inputs. It ensures alignment and maintains temporal consistency in the dynamic area. Finally, the independently learned SNS and MS module features are refined and connected to obtain a video feature with temporal consistency. This video feature is concatenated with the output from the depth embedder. The depth head then performs upsampling to generate consecutive depth maps for both frames.

3.3. Difference Mask

Figure 3 shows the process of generating the difference mask $M^d \in \mathbb{R}^{1 \times \frac{H}{8} \times \frac{W}{8}}$. To generate M^d , N_t produced by the surface normal decoder is used. These surface normal directions indicate the surface’s slope, and the set of

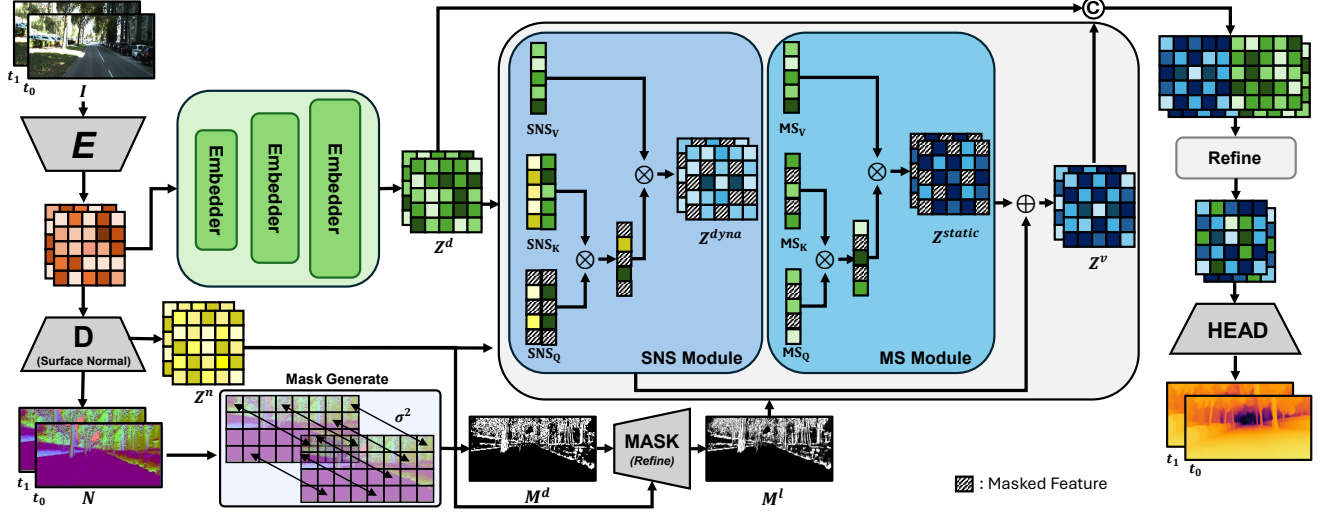


Figure 2. Overall architecture of the proposed STATIC model. The model primarily consists of an encoder, depth embedder, and video modules, with a surface normal decoder and head as submodules.

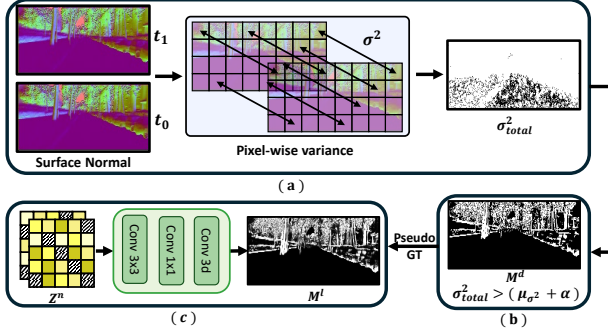


Figure 3. The process of generating the difference mask. The difference mask is updated at each step from (a) to (c). Step (a) involves pixel-wise variance calculation, (b) applies thresholding, and (c) refines the results using a pseudo-labeling process. The final mask \$M^l\$ is utilized within the model.

these directions represents the geometric characteristics of the object.

Firstly, we compute the difference in \$N_t\$ by calculating its directional variance \$\sigma^2\$. This \$\sigma^2\$ represents directional differences in terms of magnitude. To determine the total directional variance, \$\sigma^2\$ is computed pixel-wise along each axis (\$x\$, \$y\$, and \$z\$), and these values are then summed to obtain \$\sigma_{total}^2\$. this process is expressed as follows:

$$\sigma_{total}^2 = \frac{1}{N} \sum_{i=1}^N \sum_{k \in \{x, y, z\}} (v_k(i) - \mu_k)^2, \quad (1)$$

where \$N\$ is the number of pixels, \$v_k(i)\$ represents the component of the \$k\$ axis direction at each pixel coordinate, and \$\mu_k\$ represents the mean value along each axis. Secondly, the mean value \$\mu_{\sigma^2}\$ of \$\sigma_{total}^2\$ is subtracted from the variance

mask. Due to camera movement affecting all regions, \$\sigma_{total}^2\$ is non-zero even in static areas. Thus, we treat the most frequently occurring \$\sigma_{total}^2\$ in \$N_t\$ as the camera's movement and consider it as \$\mu_{\sigma^2}\$. To compensate for the camera's movement, we subtract \$\mu_{\sigma^2}\$ from \$\sigma_{total}^2\$. Furthermore, we use the learnable parameter \$\alpha\$ for a more adaptive threshold. this process is expressed as follows:

$$M^d = \begin{cases} 1 & \text{if } \sigma_{total}^2 > (\mu_{\sigma^2} + \alpha) \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Finally, to achieve a clearer outline of the mask, we use \$M^d\$ as a pseudo-label to perform refinement. The refinement utilizes \$N_t\$ and \$M^d\$ as inputs. Figure 3 (c) shows the final output mask \$M^l \in \mathbb{R}^{1 \times \frac{H}{8} \times \frac{W}{8}}\$.

3.4. Surface Normal Similarity Module

The SNS module is used to ensure temporal consistency in the dynamic area within \$M^l\$. However, \$M^l\$ represents the motion between two frames, so all movements from both frames are captured within a single mask. Therefore, to match \$M^l\$ with each frame, we create a similarity map that captures the corresponding locations between them.

As shown in Figure 4, the detailed structure of the SNS module is presented. First, the depth context feature \$Z_t^d\$ and surface normal feature \$Z_t^n\$ are concatenated along the channel axis to form \$Z_t^s \in \mathbb{R}^{L_t \times (C_t^d + C_t^n)}\$, where \$L_t\$ represents the total number of pixels \$\frac{H}{8} \times \frac{W}{8}\$ for each frame.

\$Z_0^s\$ multiplied by \$M^l\$ is used as the query feature, and \$Z_1^s\$ as the key feature. After performing the dot product between the query feature and the key feature, softmax is applied to obtain the location similarity map \$S \in \mathbb{R}^{L_0 \times L_1}\$ based on the location similarity between features within

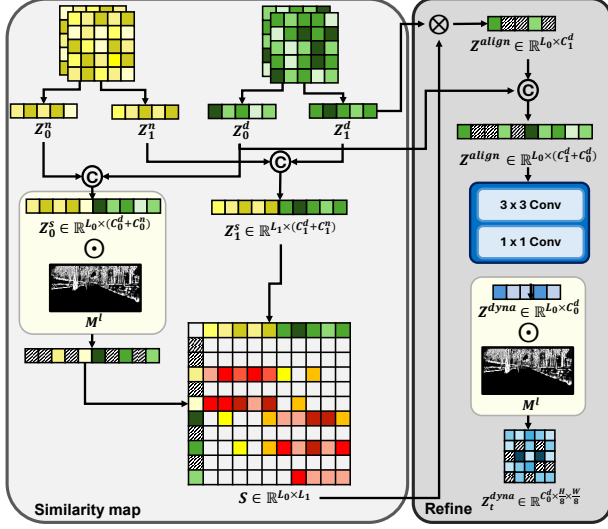


Figure 4. The structure of the SNS module. First, a similarity map S is generated using two features. Then, by multiplying this map with the depth features of other frames, a process similar to warping is performed.

M^l . The depth feature is used to obtain distance similarity, while the surface normal feature is used to obtain geometric similarity. Therefore, in dynamic areas of M^l with low correlation, each frame’s similarity decreases, allowing alignment. this process is expressed as follows:

$$S = \text{softmax}((Z_0^s \odot M^l) \cdot Z_1^{s\top}), \quad (3)$$

where $Z_0^s \in \mathbb{R}^{L_0 \times (C_0^d + C_0^n)}$ and $Z_1^{s\top} \in \mathbb{R}^{(C_1^d + C_1^n) \times L_1}$. By using the depth context feature $Z_1^d \in \mathbb{R}^{L_1 \times C_1^d}$ as the value feature with S , the aligned feature $Z_{align} \in \mathbb{R}^{L_0 \times C_1^d}$ can be obtained. This results in mapping the next frame depth context C_1^d to the corresponding locations L_0 in the current frame. Finally, the SNS module learns the dynamic temporal consistency $Z_t^{dyna} \in \mathbb{R}^{C \times \frac{H}{8} \times \frac{W}{8}}$ by concatenating and refining the first frame Z_0^d and the aligned frame Z_{align} . This enables the SNS module to comprehend depth variations in dynamic areas. In the same manner, the process is repeated with the frames in reverse order.

3.5. Masked Static Module

As shown in Figure 5, the detailed structure of the MS module is presented. $(1 - M^l)$ refers to the static area of the frames. Multiplying Z_t^d with $(1 - M^l)$ results in retaining only the aligned area. Therefore, we multiply the static area $(1 - M^l)$ by the depth context feature Z_t^d for each frame. The MS module follows a cross-attention structure $CrossAttn(Q, K, V)$. To capture the correlation between the frames, the query feature is derived from Z_0^d , while the key and value features are taken from Z_1^d . This process yields results similar to warping in the same area, and we

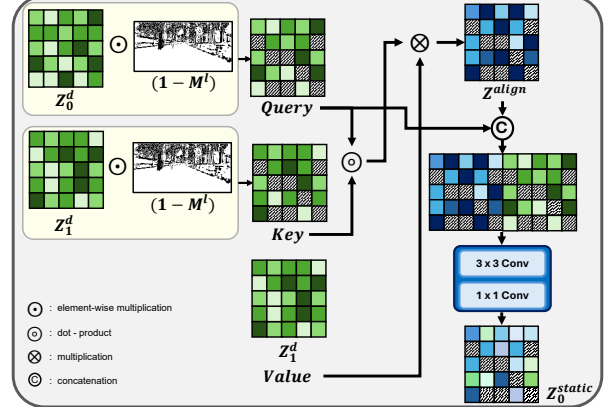


Figure 5. The structure of the MS module. First, an attention mechanism is applied using masked features that retain only the static area. Next, a refinement process is conducted to integrate the aligned feature with the depth feature.

repeat this procedure in reverse order for the frames in the same manner to obtain aligned static features. Finally, the aligned features and query features are concatenated and processed through a refinement process using a simple convolutional structure. Therefore, we obtain static temporal consistency $Z_t^{static} \in \mathbb{R}^{C \times \frac{H}{8} \times \frac{W}{8}}$. this process is expressed as follows:

$$Z_t^{static} = \text{conv}(\text{concat}(Z_t^{align}, Z_t^d \odot (1 - M^l))), \quad (4)$$

where Z_t^{align} is aligned static features.

Then, the independently learned features, Z_t^{static} and Z_t^{dyna} , are combined to form a unified video feature Z_t^v .

3.6. Loss function

Following previous works [20, 52], we use a scaled version of the Scale-Invariant loss (SILog) [7] to train the depth map. In addition, we use Mean Squared Error (MSE) to supervise the surface normal. Similarly, MSE is also employed in the process of generating the refined difference mask M^l . The M^l generation loss is defined as follows:

$$L_{mask} = \frac{1}{N} \sum_{i=1}^N (M^d(i) - M^l(i))^2, \quad (5)$$

where N denotes the total number of pixels within the difference mask. Therefore, each loss term is combined into a total loss, with the MSE loss terms weighted by a factor of α . this process is expressed as follows:

$$L_{total} = L_{Depth} + \alpha \cdot L_{Normal} + \alpha \cdot L_{Mask}, \quad (6)$$

where L_{Depth} is SILog, while L_{Normal} and L_{Mask} are MSE. Following [20], we use the SILog parameter $\lambda = 0.85$. In addition, we set $\alpha = 10$.

Method	Frame	C	O	M	Abs Rel ↓	Sq Rel ↓	RMSE ↓	$\delta < 1.25 \uparrow$	$\delta < 1.25^2 \uparrow$	$\delta < 1.25^3 \uparrow$
PEM [21]	SF	-	-	-	0.068	0.221	2.127	0.958	0.993	0.9983
AdaBins [4]	SF	-	-	-	0.058	0.190	2.360	0.964	0.995	0.9993
BinsFormer [24]	SF	-	-	-	0.058	0.190	2.336	0.964	0.996	0.9994
DepthFormer [1]	SF	-	-	-	0.053	0.187	2.285	0.970	0.996	0.9994
PixelFormer [2]	SF	-	-	-	0.052	0.152	2.093	0.975	0.997	0.9994
GEDepth [49]	SF	✓	-	-	0.049	0.143	2.048	0.976	0.997	0.9994
NeuralRGB [25]	MF	✓	-	-	0.100	-	2.829	-	-	-
ST-CLSTM [53]	MF	-	-	✓	0.101	-	4.137	0.890	0.970	0.9890
FlowGRU [8]	MF	-	✓	✓	0.112	0.070	4.260	0.936	0.983	0.9930
Flow2Depth [47]	MF	✓	✓	-	0.109	-	4.284	0.910	0.980	0.9900
RDE-MV [31]	MF	-	-	✓	0.111	0.821	4.650	0.898	0.972	0.9890
FMNet [43]	MF	-	-	-	0.069	0.342	3.340	0.946	0.986	0.9960
ManyDepth-FS [45]	MF	✓	-	-	0.053	0.243	2.248	0.975	0.997	0.9994
TC-Depth-FS [37]	MF	-	-	-	0.059	0.249	3.280	0.947	0.985	0.9940
MAMo [50]	MF	-	✓	✓	0.049	0.130	1.989	0.977	0.998	0.9995
STATIC	MF	-	-	-	0.048	0.137	1.977	0.979	0.998	0.9994

Table 1. Performance comparison between various methods on the KITTI Eigen dataset. The best results are in bold. "MF" indicates multi-frame methods, "SF" indicates single-frame methods, "O" represents optical flow, "C" represents camera parameter, and "M" represents memory.

4. Experiments

4.1. Evaluation Metrics

We employ standard evaluation metrics, including Average Relative Error (Abs Rel), Root Mean Squared Error (RMSE), Threshold Accuracy (δ) at thresholds 1.25, 1.25², and 1.25³, and Square Relative Error (Sq Rel).

Additionally, we use a metric s from Li et al. [23] for evaluating temporal consistency. This metric is as follows:

$$qTC_t = \frac{1}{\sum(K_t == 1)} \sum K_t \left| \frac{D_t - D_t^w}{D_t} \right|,$$

$$rTC_t = \frac{1}{\sum(K_t == 1)} \sum K_t \left[\text{Max} \left(\frac{D_t}{D_t^w}, \frac{D_t^w}{D_t} \right) < \text{thr} \right],$$

where D_t is the predicted depth, D_t^w is the warped depth from D_{t-1} , and K_t is a depth validity mask. We use Flowformer [16] as the optical flow model for warping. We use this metric to present the temporal consistency comparison results in Table 3.

4.2. Datasets

KITTI Eigen: The KITTI dataset [13] is among the most frequently utilized benchmarks for outdoor depth estimation. In our approach, we adopt the Eigen split for training and testing, which includes 23,488 training images and 697 test images. Video sequences corresponding to these training and test images are utilized, with each video frame having a resolution of 375×1241 pixels. For evaluating the test set, we apply the crop defined by Garg et al. [11], and depth estimation is performed up to a distance of 80 meters.

NYU Depth v2: NYU v2 [39] is a well-known indoor dataset, providing 120,000 RGB and depth image pairs (480×640 resolution) collected as video sequences across 464 indoor environments. For video-based evaluation, we adapted the dataset by employing the test approach adopted by [44]. Specifically, we used 249 scenes from the original 464 scenes, comprising pairs of RGB and sync depth images [20] for training. The remaining 215 scenes containing 654 images were used for testing. Each depth map is limited to a maximum range of 10 meters, and we apply center cropping as suggested by Eigen et al. [7].

4.3. Result

Results on KITTI: Table 1 presents our results on the KITTI dataset, where STATIC demonstrates robust performance with minimal input requirements. We compare our approach against various state-of-the-art multi-frame and single-frame methods. Even without camera parameters, additional memory, or optical flow, our model achieves competitive results across all metrics. Our model's depth embedder is based on PixelFormer [2] and outperforms the baseline, highlighting the effectiveness of the temporal consistency module. Furthermore, our approach improves RMSE by approximately 0.60% over the recently proposed MAMo [50], even though MAMo uses more frames. These results indicate that our model effectively preserves consistency in independent areas, even in the presence of substantial movement within outdoor environments.

Results on NYU v2: Table 2 presents our results on the NYU v2 dataset. Following the evaluation procedure of [2] and without additional training data, our method

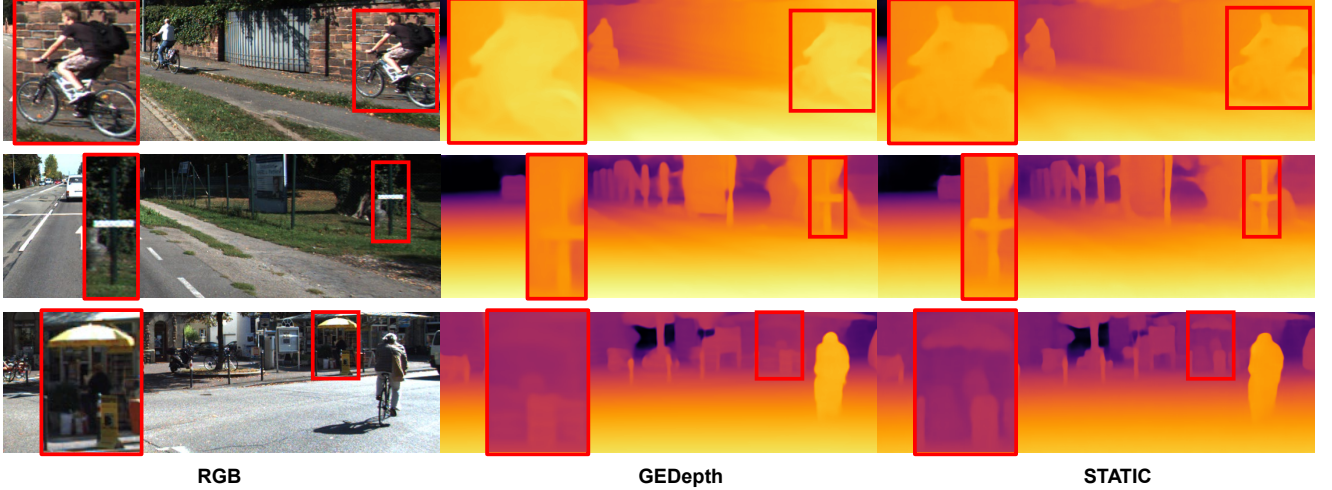


Figure 6. Qualitative comparison of video methods on the KITTI Eigen dataset.

Type	Method	$\delta < 1.25 \uparrow$	Abs Rel $\downarrow$
SF	Midas-v2.1-Large [34]	0.910	0.095
	DPT-Large [35]	0.928	0.084
MF	WSVD [42]	0.768	0.164
	ST-CLSTM [53]	0.833	0.131
	DeepV2D [40]	0.924	0.082
	FMNet [43]	0.832	0.134
	VITA [46]	0.922	0.092
	MAMo [50]	0.919	0.094
MF	STATIC	0.934	0.087

Table 2. Performance comparison between various methods on the NYU v2 dataset.

achieves state-of-the-art performance on the $\delta < 1.25$ metric. Specifically, our model demonstrates a 1.63% improvement over the recently proposed MAMo method on $\delta < 1.25$ and a 0.65% gain over the previous state-of-the-art. Furthermore, our model shows effective improvements on the Abs Rel metric compared to other multi-frame methods.

Qualitative Results: Figure 11 demonstrates that STATIC considerably improves depth estimation compared to other video methods. The regions separated by M^l are created through computation, indicating that even small and distant movements are taken into account. In the bottom sample, the result from our model successfully distinguishes the depth of a distant parasol, emphasized by the red box. Additionally, learning in independent areas enables a better understanding of diverse depth variations in dynamic areas, producing clearer results. This clarity is evident in the sharpness of objects like the bicycle and person in the first sample, and the sign in the second sample.

Temporal Consistency: Table 3 presents a numerical comparison across various methods using standard evaluation

metrics to assess temporal consistency. Notably, our approach achieves a 1.76% improvement in relative Temporal Consistency (rTC) compared to the previous highest performance. Moreover, an impressive 12.79% increase is observed in absolute Temporal Consistency (aTC). These findings emphasize the substantial contribution of independent area learning in enhancing temporal consistency, demonstrating that even a small number of frames, in this case only two, can yield significant improvements in maintaining stable predictions over time. Further insights are provided by Figure 10, which shows qualitative comparisons across 60 consecutive frames, illustrating each method’s ability to maintain temporal consistency over time. Competing methods often display striping artifacts, indicating instability in estimated depth. In contrast, STATIC shows a reduction in both the occurrence and intensity of these artifacts, highlighting its stability in maintaining temporal consistency over an extended sequence. These results demonstrate STATIC’s ability to provide reliable depth estimations, contributing to smoother transitions and improved visual coherence across frames.

4.4. Ablation Study

Effect of MS module: Table 4 demonstrates the effectiveness of each module. The MS module primarily serves to maintain temporal consistency in static areas. Since static areas occupy the majority of the scene, removing the MS module increases the regions where temporal consistency cannot be learned, leading to a decline in RMSE performance of 1.57%. This result underscores the significance of the MS module in sustaining overall performance.

Effect of SNS module: The SNS module contributes to temporal consistency in dynamic areas, focusing on aligning contours and smaller regions with significant motion within the image. Since these small, high-motion areas

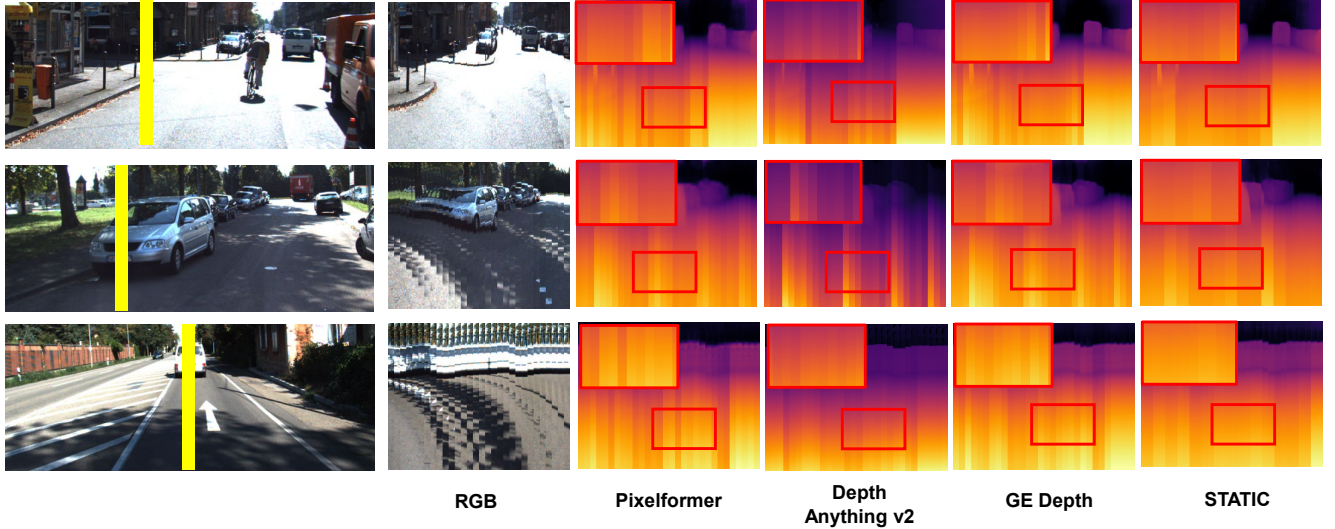


Figure 7. Temporal consistency qualitative comparison of previous methods on the outdoor KITTI Eigen dataset.

Type	Method	rTC $\uparrow$	aTC $\downarrow$
SF	NeWCRFs [52]	0.914	0.116
	iDisc [33]	0.923	0.108
	GEDepth [49]	0.919	0.133
	Depth Anything V2 [48]	0.946	0.099
MF	TC-Depth-FS [37]	0.901	0.122
	Many-Depth-FS [45]	0.920	0.111
	NVDS [44]	0.951	0.096
	MAMo [50]	0.966	0.086
MF	STATIC	0.983	0.075

Table 3. Comparison of temporal consistency across various methods on rTC and aTC.

SNS	MS	Abs Rel $\downarrow$	RMSE $\downarrow$	$\delta < 1.25 \uparrow$
-	-	0.051	2.022	0.977
✓	-	0.050	2.008	0.978
-	✓	0.050	1.989	0.978
✓	✓	0.048	1.977	0.979

Table 4. The ablation experiment evaluates the individual effects of the SNS module and the MS module on the KITTI Eigen dataset.

have a limited impact on the whole image, the removal of the SNS module leads to a smaller RMSE drop of 0.61% compared to the MS module. Given that the model learns each area independently before integrating them, the absence of one module introduces empty regions, thereby reducing overall performance. Thus, the ablation study illustrates that the combined use of both modules, with their independent learning and integration, is essential to enhance performance, highlighting the importance of including all modules.

4.5. Limitations

Our model utilizes surface normal to separate regions, as surface normals and depth share common features and are intrinsically related. Consequently, a decline in the performance of either can significantly impact the model’s overall performance. Therefore, maintaining a balance between surface normal and depth during training is essential. When one side becomes overly dominant, effective learning is hindered, leading to decreased training stability. Additionally, our model requires supervision on surface normal during the training stage, which makes it necessary to pre-compute surface normal from the depth map using a Sobel-like filter. Furthermore, our model achieves temporal consistency by using modules based on depth context features generated by a depth embedder. These features require sufficient quality to maintain temporal consistency, as they heavily depend on the encoder and depth embedder performance. As a result, the temporal consistency of the SNS and MS modules is significantly dependent on the encoder’s performance.

5. Conclusion

The STATIC model addresses the problem of temporal consistency in video monocular depth estimation without relying on additional motion information. Ablation studies confirm the efficiency of using both the Surface Normal Similarity (SNS) and Masked Static (MS) modules, which independently handle dynamic and static areas. Our mask leverages surface normals to capture geometric structures, maintain frame alignment, and reduce prediction errors. This approach leads to improved temporal consistency on datasets like KITTI and NYUv2. The independent learning strategy demonstrates superior accuracy and achieves high performance without additional inputs.

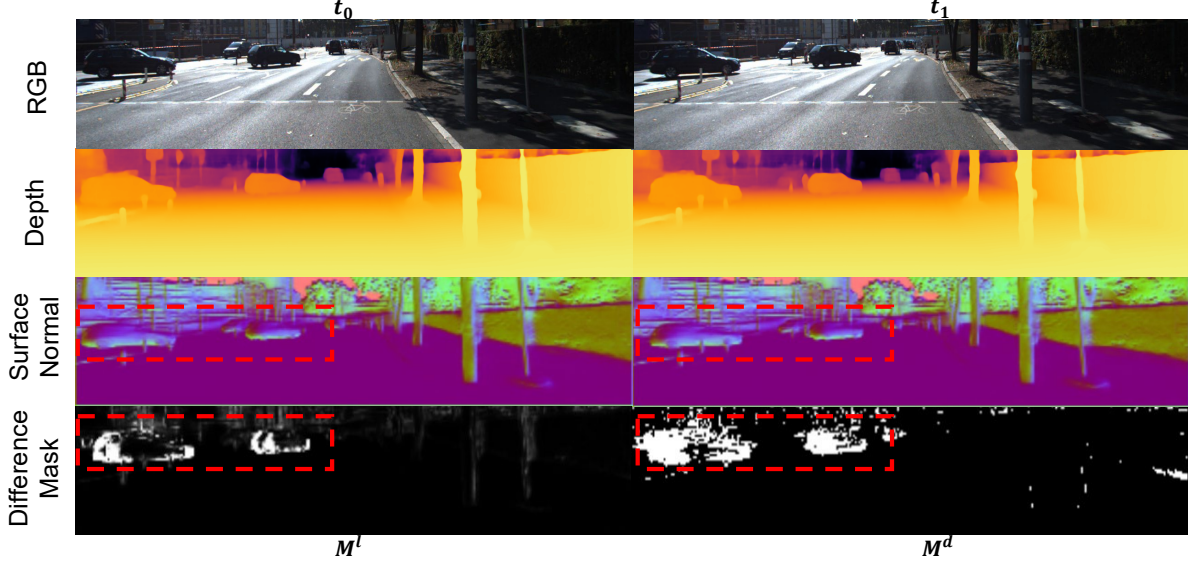


Figure 8. Results of STATIC in a scenario where the camera is stationary, and only the object is moving.

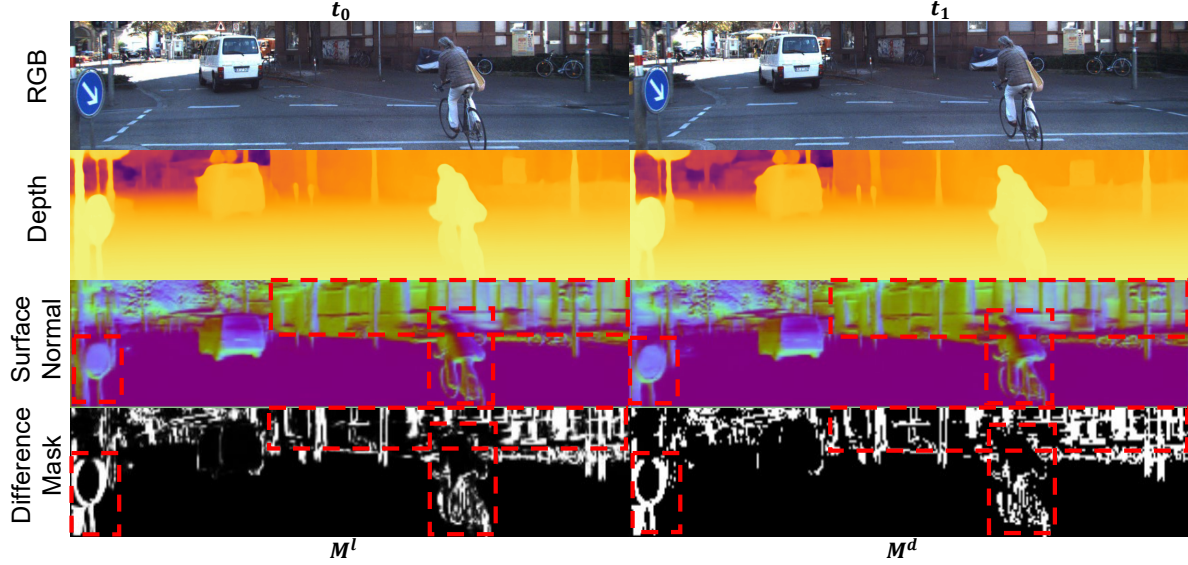


Figure 9. Results of STATIC in a scenario where both the camera and the object are moving.

6. Appendix

7. Implementation Details

The proposed method is implemented using the AdamW [29] optimizer with β parameters of 0.9 and 0.999, a batch size of 2 with 2 frames per batch, and a weight decay set to 10^{-2} . We train the model over 20 epochs on both the KITTI and NYUv2 datasets, starting from an initial learning rate of 4×10^{-5} , which linearly decays to 4×10^{-6} over the training process. With four NVIDIA 4090 GPUs, each epoch takes approximately 60 minutes. The encoder backbone is initialized with pre-trained Swin2-L [26] weights. During testing, final

depth predictions are obtained by averaging the outputs from both the original and mirrored inputs. We employ a training and testing protocol same to those used in [2, 20].

8. Model Architecture Details

We provide a more detailed explanation of our model architecture. In this paper, we employ the Swin Transformer V2 [26] as the encoder. For depth embedding, we utilize the Pixelformer’s decoder [2], which is known for its powerful depth decoding capabilities. Additionally, the features processed by the depth embedder are passed through the SNS and MS temporal consistency modules. Each of these modules utilizes the SAM block proposed in the Pixelformer,

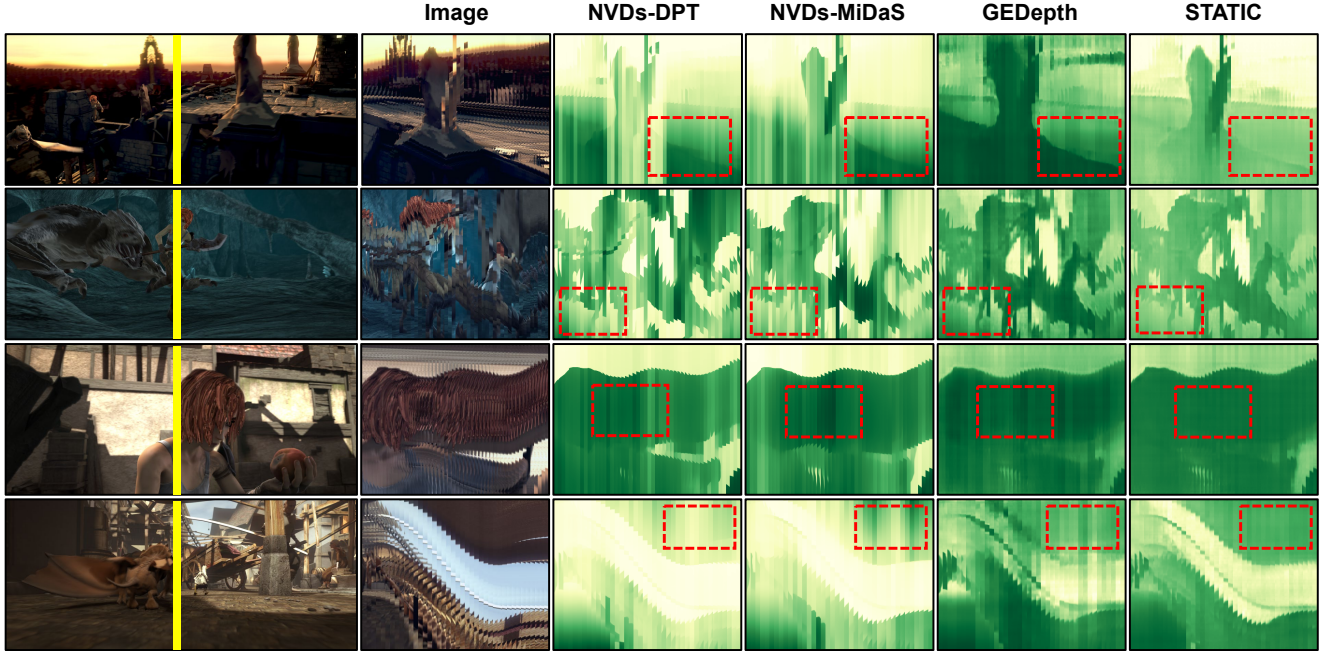


Figure 10. Qualitative comparison of video methods on the MPI-Sintel dataset. Depth results are aligned along the yellow line across all frames for comparison.

which has been modified to align with the temporal consistency requirements of our model. The SAM block, based on the Swin block, enables the SNS and MS modules to operate as attention mechanisms driven by a window-based structure. Moreover, we set the window size of the SNS module larger than that of the MS module, allowing the SNS module to capture information from more distant regions, while the MS module focuses on closer areas. Finally, the model generates the final depth map through up-sampling and simple convolution layers.

9. Surface Normal Ground Truth Generation

We employ supervised learning for surface normals, which requires ground truth (GT) data. To simplify GT acquisition, we generate surface normal GT by applying a Sobel filter [18] to the depth map. A depth map provides z-axis information for each pixel, while the Sobel filter computes gradients in the x and y directions through differential operations. Combining these values yields the normal vector at each pixel, defining the surface orientation. However, radar-based depth maps are very sparse, making it difficult to apply the Sobel filter effectively. To address this limitation, we first generate a dense depth map using Depth Anything V2 [48]. Importantly, surface normals do not require temporally consistent depth; they only depend on the consistency of depth shapes. Thus, generalization performance is especially critical in this context. Finally, we apply the Sobel filter to the dense depth map to obtain the surface

Method	Type	$\delta_1 \uparrow$	$Rel \downarrow$	$OPW \downarrow$	$T(ms)$
DPT [35]	Image	0.597	0.339	0.612	67.7
Midas [34]		0.485	0.410	0.843	53.0
CVD [30]	Flow	0.518	0.406	0.497	-
WSVD [42]		0.501	0.439	0.577	296.6
Robust-CVD [19]	Camera	0.521	0.422	0.475	-
GEDepth [†] [49]		0.522	0.430	0.473	185
ST-CLSTM [53]	Memory	0.351	0.517	0.585	40.5
FMNet [43]	Video	0.357	0.513	0.521	270.3
DeepV2D [40]		0.486	0.526	0.534	975.68
NVDS-Midas [44]		0.532	0.374	0.469	108.4
NVDS-DPT		0.591	<u>0.335</u>	<u>0.424</u>	120.76
Ours	Video	0.598	0.330	0.405	197.32

Table 5. Performance comparison of various methods on the Sintel dataset. The best results are highlighted in **bold**, and the second best results are underlined. Note that [†] indicates retrained model and T denotes inference time.

normal ground truth.

10. Additional Experiments

10.1. MPI-Sintel Dataset

We evaluate our method on the MPI-Sintel dataset [5], which consists of 23 synthetic sequences of dynamic scenes with ground-truth depth in metric scale. The dataset provides two rendering variants, clean and final, the latter in-

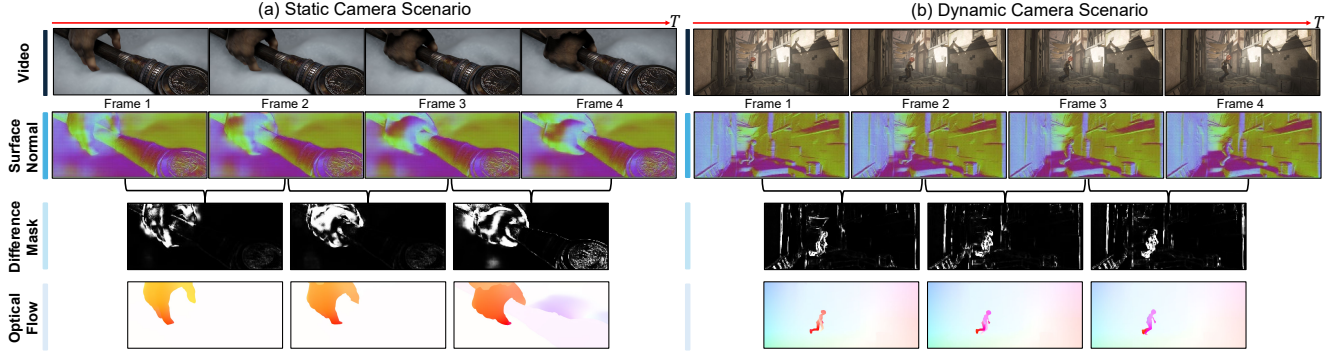


Figure 11. Qualitative comparison of static and dynamic camera scenarios. Video frames, surface normal, and the corresponding difference mask across consecutive frames are shown, with optical flow for comparison.

cluding realistic effects such as motion blur and haze. While Sintel is synthetic, incorporating unlabeled real world images has been shown to greatly improve generalization across test sets.

10.2. Evaluation Metric

We evaluate our method using both depth accuracy and temporal consistency. For depth accuracy, we report standard metrics such as Relative Error (Rel) and Threshold Accuracy ($\delta < 1.25$), following the same protocol as prior methods. To measure temporal consistency, we follow FM-Net [43] and adopt the optical flow-based warping metric (OPW).

10.3. Quantitative Results

Table 5 presents our results on the Sintel dataset [5]. Following the evaluation procedure of [44], we compare against representative image, flow, camera, and memory-based baselines. Our method achieves the best performance in $\delta < 1.25$, *Rel*, and *OPW*, demonstrating high accuracy with competitive inference time together with temporal consistency. Compared with prior video-based approaches such as NVDS [44], our model achieves a significant improvement in *OPW*, indicating enhanced robustness in maintaining temporal consistency. These results highlight the effectiveness of our video driven strategy in capturing temporal coherence while maintaining competitive depth accuracy. This improvement is primarily attributable to surface normals, which provide consistent geometric cues that preserve fine grained boundaries and contribute to higher performance. In addition, the resulting difference masks help reinforce temporal consistency. Consequently, these cues enable more stable depth alignment across frames.

10.4. Qualitative Results

Figure 10 provides a qualitative comparison across all frames of each scene to illustrate temporal consistency. While the compared approaches often exhibit striping pat-

terns that reflect temporal inconsistencies in the estimated video depth, STATIC considerably reduces both the frequency and intensity of these striping patterns over long sequences. In addition, beyond background stability, our model maintains structural consistency more effectively than the compared methods. This advantage arises from the difference mask, which explicitly highlights structural changes and enables the model to preserve consistency in geometric details over longer sequences. Especially in the first scene, STATIC also demonstrates superior geometric consistency, producing sharp results without edge ambiguity or shape distortion. These observations indicate that STATIC produces reliable monocular video depth estimates, enabling smoother frame to frame transitions and improved visual consistency.

11. Robustness of the Difference Mask

Figure 11 illustrates that surface normal-based difference mask effectively capture structural changes under both static and dynamic camera conditions. Surface normals remain highly consistent across frames, which provides a foundation for generating difference masks by detecting variations in normal directions at each pixel.

In Figure 11 (a), the difference mask highlights only the moving hand while the background remains unchanged, producing regions that align well with optical flow. In Figure 11 (b), where the camera is moving, differences also appear in the background, while the motion of the person aligns well with optical flow.

A key distinction from optical flow is that the proposed difference mask isolates truly changing regions rather than modeling global scene motion. In optical flow, this global motion appears as large areas on the right shaded in blue and on the left shaded in red, compared to the more structural background changes captured by the difference mask. This behavior can also be observed in Figure 4 (a) between frames 3 and 4 at the cane. By explicitly separating dynamic and static regions, our method enforces consistency

<i>FrameSpeed</i>	$\delta_1 \uparrow$	<i>Rel</i> $\downarrow$	<i>OPW</i> $\downarrow$
$\times 1$	0.598	0.330	0.405
$\times 0.5$	0.595	0.334	0.411
$\times 0.33$	0.571	0.359	0.424

Table 6. Performance Evaluation at Different Frame Speeds.

only where structural changes occur, rather than aligning all background areas globally as in optical flow. This targeted enforcement enables STATIC to preserve structural fidelity while maintaining temporal consistency, reducing the risk of artifacts in regions that remain static. In addition, treating dynamic and static regions independently improves performance, as each module can specialize in the characteristics of its respective area. Overall, STATIC achieves temporal consistency more efficiently by focusing only on genuinely moving regions while maintaining stability in unchanged areas.

12. Selection of Comparable Baselines

In this section, we provide explanations for several recent state-of-the-art baselines that are not included in our main comparison, as their training settings differ substantially from standard benchmarks.

Depth Anything V2 [48] is trained on about 595K synthetic labeled images and more than 62M real unlabeled images. This web-scale supervision greatly improves generalization and boundary sharpness, but places it in a different category from methods trained only on KITTI [13] or Sintel [5]. DepthCrafter [15] employs an image to video diffusion backbone and large scale synthetic and real data, enabling predictions across sequences of up to 110 frames. Its dependence on diffusion priors and extended temporal context separates it from benchmark-based approaches. ECoDepth [32] conditions a diffusion backbone [36] on ViT embeddings and leverages large scale pretraining for zero shot transfer, benefiting from foundation model representations not available in our setting.

As these methods rely on web-scale supervision or diffusion-based generative modeling, our comparison instead focuses on state of the art methods trained under comparable conditions, ensuring fairness in evaluation.

13. Dependency of Frame Rate

In this section, we demonstrate the robustness of the proposed model under various FPS settings in video sequences. Table 6 reports the results obtained by varying frame speed through skipping intermediate frames. The results show that overall performance does not drop significantly, and in particular, OPW which reflects temporal consistency shows only minimal differences. Furthermore, Figure 12 visualizes the difference masks when the frame interval is in-

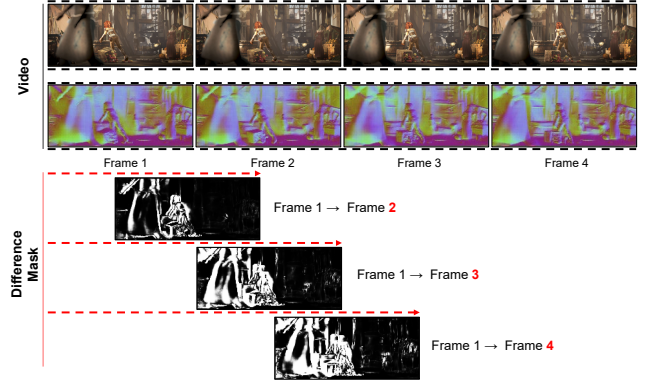


Figure 12. Comparison of Difference Mask Variations with Increased Frame Intervals.

creased. Even at lower frame speeds, the masks still accurately capture static and dynamic regions. This demonstrates that our difference mask is not overfitted to a specific FPS but instead computed from surface normals, ensuring stable performance across different frame speeds as long as the surface normals remain undistorted.

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