D³FlowSLAM: Self-Supervised Dynamic SLAM with Flow Motion Decomposition and DINO Guidance

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Abstract

In this paper, we introduce a self-supervised deep SLAM method that robustly operates in dynamic scenes while accurately identifying dynamic components. Our method leverages a dual-flow representation for static flow and dynamic flow, facilitating effective scene decomposition in dynamic environments. We propose a dynamic update module based on this representation and develop a dense SLAM system that excels in dynamic scenarios. In addition, we design a self-supervised training scheme using DINO as a prior, enabling label-free training. Our method achieves superior accuracy compared to other self-supervised methods. It also matches or even surpasses the performance of existing supervised methods in some cases. All code and data will be made publicly available upon acceptance.

Introduction

Simultaneous localization and mapping (SLAM) is fundamental to the fields of computer vision and robotics, with applications ranging from augmented reality (AR) and virtual reality (VR) to autonomous driving. In AR, SLAM is commonly used for accurate localization of agents, enabling users to place virtual objects (Ye et al. 2021), while dense reconstruction is crucial for better interaction with the surrounding environment. Due to the simplicity of monocular video acquisition, monocular dense SLAM (Czarnowski et al. 2020; Tateno et al. 2017) has attracted significant attention, although it remains a more complex task compared to RGB-D SLAM (Wang et al. 2021; Yan et al. 2022; Yu et al. 2018; Dai et al. 2020; Henein et al. 2020). Significant progress has been made in sparse traditional (Engel, Schops, and Cremers 2014; Mur-Artal, Montiel, and Tardos 2015; Forster, Pizzoli, and Scaramuzza 2014; Engel, Koltun, and Cremers 2017a), learning-based (Zhou et al. 2017; Wang et al. 2018, 2019), and hybrid (Wang, Yuan, and Xie 2017; Tateno et al. 2017; Brahmbhatt et al. 2018) approaches. More recently, a learning-based monocular dense SLAM system, DROID-SLAM (Teed and Deng 2021a), has been proposed. It demonstrates better accuracy and robustness than other methods but requires extensive labeled data, such as camera poses and depths, during training, which limits its adaptability for new scenes.

Developing robust SLAM methods for real-world AR applications presents significant challenges, particularly in dynamic environments. For instance, we find that dynamic objects can create ambiguity during flow residual estimation in (Teed and Deng 2021a), which often results in suboptimal performance. To address these challenges, some approaches (Bescos et al. 2018; Xiao et al. 2019) pre-filter dynamic objects using segmentation before executing monocular sparse SLAM. Other strategies (Yang and Scherer 2019; Huang et al. 2020) integrate object detection with SLAM to mitigate these issues. However, these methods often encounter limitations in practical scenarios, as the system’s generalization capability is restricted by the training data of the detector, leaving some dynamic objects unaddressed (Wang et al. 2021). If the detector generates inaccurate outputs, the system may fail entirely. Furthermore, many of these approaches are tightly coupled with sparse SLAM, with limited focus on dense SLAM. Directly ignoring dynamic information and concentrating solely on sparse systems can lead to the loss of valuable data.

Building on previous work, we argue that a dense dual-flow representation can effectively address these challenges. This approach offers several benefits: 1) it optimizes poses and depths using static flows in a standard manner, 2) it learns dynamic flows by maintaining consistent luminosity through warping the current frame to adjacent frames, and 3) it fully utilizes information from all pixels during estimation. Furthermore, this flow-based representation facilitates the development of a self-supervised training scheme for our model. With these concepts in mind, we introduce D³FlowSLAM, a dense method that incorporates a dynamic update module based on dual-flow representation, as shown in Fig. 1. We leverage the self-supervised model DINO (Caron et al. 2021) to obtain a prior foreground mask by clustering its features (Amir et al. 2021). Then, in the update module, we employ a dynamic mask branch guided by two priors: the foreground mask generated from DINO features and a mask derived from the dual-flow difference. This update process is detailed in Fig. 2.

Our method effectively harnesses information from different regions of the pixels, resulting in more accurate estimations in dynamic scenes. Lastly, we design a self-supervised training scheme that enables the exploitation of an unlimited amount of unlabeled data and finetuning on new im-
Figure 1: D³ FlowSLAM Overview. D³ FlowSLAM takes an image sequence as input, extracts features to construct a correlation volume, and then combines this with the initial static flow, dynamic flow, and dynamic mask before feeding it into the dynamic update module. This module iteratively optimizes the residuals of pose, inverse depth, static flow, dynamic flow, and dynamic mask, ultimately providing estimates of the camera pose, 3D structure, and dynamic decomposition results.

**Related Work**

**Dynamic SLAM**

Humans live in a dynamic environment, intelligent systems should also have the ability to deal with dynamic environments, recognizing the dynamic contents from the static environments. Traditional approaches primarily mitigate the interference of dynamic objects by introducing a prior (Tan et al. 2013) or RANSAC methods (Huang et al. 2020a). Some recent approaches try to use segmentation methods like (He et al. 2017) to filter out potential dynamic objects like vehicles and pedestrians (Vincent et al. 2020; Bescos et al. 2018; Xiao et al. 2019) and then run the sparse SLAM system like (Mur-Artal, Montiel, and Tardos 2015), or unify object detection and SLAM into a multi-task system (Huang et al. 2020b; Nair et al. 2020; Ye et al. 2023), or add the object constraint to the SLAM system (Yang and Scherer 2019; Strecke and Stuckler 2019; Brasch et al. 2018) to eliminate the interference of dynamic objects. Overall, the aforementioned methods primarily address the problem of localization and mapping in dynamic scenes by adding auxiliary modules to traditional sparse SLAM systems. In contrast, our method takes an end-to-end approach, integrating the identification of dynamic regions and pose optimization within a single dense framework for joint optimization. Similar to (Zhan et al. 2021; Teed and Deng 2021a), our learning-based approach can identify dynamic fields at the pixel level, allowing for more effective use of image information and better simulating how humans perceive the world.

**Self-Supervised Learning in Vision**

Self-supervised learning has recently advanced in computer vision, enabling models to autonomously learn high-quality features from large image datasets (He et al. 2020, 2022; Oquab et al. 2013; He et al. 2020, 2022; Oquab et al. 2013; He et al. 2020). In specific tasks like optical flow estimation, the predictions of self-supervised methods (Meister, Hur, and Roth 2018; Luo et al. 2021) have progressively approached the accuracy of supervised methods. These methods utilize photometric loss to supervise their networks, eliminating the need for optical flow labels. Other works, such as (Bello and Kim 2023; Feng et al. 2022; Sun and Hariharan 2024), have also tried to address consistent depth prediction in a self-supervised manner. Dynamo-Depth (Sun and Hariharan 2024) is one of the few self-supervised methods that can provide pose estimation, but its results are quite poor. We integrate the aforementioned self-supervised techniques by combining photometric loss with features derived from DINO (Caron et al. 2021). This integration supervises the estimation of camera poses, depths, and the recognition and decomposition of dynamic regions within images, enabling our method to significantly outperform other self-supervised methods in SLAM tasks.

**Scene Motion Decomposition**

Scene motion estimation captures the 3D structure and dynamics of environments, gaining increasing attention in 3D perception. Various methods have been developed using different input data types, such as 3D point clouds (Liu, Qi, and Guibas 2018; Gu et al. 2019), stereo images (Huguet and Devernay 2007; Vogel, Schindler, and Roth 2013; Zhang and Kambhamettu 2001), and RGB-D images (Hornacek,
Fitzgibbon, and Rother 2014; Hadfield and Bowden 2011; Lv et al. 2018; Quiroga et al. 2014). EffiScene (Jiao, Tran, and Shi 2021) jointly learns optical flow and motion segmentation for scene flow estimation. Monocular scene motion estimation remains less explored due to its highly ill-posed nature (Brickwedde, Abraham, and Mester 2019). We focus on monocular videos, framing scene motion estimation as the optical flow (Dosovitskiy et al. 2015; Ilg et al. 2017; Sun et al. 2018; Ranjan et al. 2019) problem. While RAFT (Teed and Deng 2020) is efficient in optical flow estimation, it doesn’t consider scene motion decomposition. Based on these works, we decide to decompose optical flow into a static field from camera motion and a dynamic field from object motion, leveraging scene flow properties (Baur et al. 2021) to provide motion information for each pixel.

**Method**

Fig. 1 provides an overview of D³FlowSLAM, which processes a sequence of images to produce both the camera pose estimation and the 3D map of the environment. It features an end-to-end differentiable architecture that integrates the strengths of traditional and learning-based approaches. The dual-flow representation enables robust handling of challenging scenarios, including dynamic scenes. Additionally, we design a self-supervised scheme to train our model without labels.

**Preliminaries: DROID-SLAM**

DROID-SLAM (Teed and Deng 2021a) is a deep dense SLAM method. It processes a sequence of images \( \{I_t\}_{t=0}^N \) using a image encoder to extract correlation features from the images. It maintains two key state variables for each image \( t \): the camera pose \( G_t \in SE(3) \) and the inverse depth \( d_t \in \mathbb{R}_+^2 \). These variables are iteratively updated with each new frame. It uses the dense correspondence field to compute the static flow residual \( p_{ij} - p_{ij} \), which is caused by the camera motion. A frame graph \( G = (V, E) \) is used to indicate co-visibility between frames, where each node corresponds to an input image. An edge \( (i, j) \in E \) represents that the images \( I_i \) and \( I_j \). The frame graph is built and updated dynamically during training and inference. Specifically, after updating each pose and depth using the static flow residual field, the frame graph is adjusted to incorporate new co-visibility relationships. For detailed information, please refer to their paper or our appendix.

**Dual-Flow Representation**

The core concept of our approach is the dual-flow representation coupled with a self-supervised training scheme. Unlike the method in (Teed and Deng 2021a), which uses a simple single-flow representation, our approach decomposes optical flow into two components: static flow driven by camera motion, and dynamic flow driven by the movement of dynamic objects, as depicted in Fig. 2. The optical flow \( F_{ot} \in \mathbb{R}^{H \times W \times 2} \), static flow \( F_{st} \in \mathbb{R}^{H \times W \times 2} \) and dynamic flow \( F_{dt} \in \mathbb{R}^{H \times W \times 2} \) are a set of vectors, where the
static flow plus the dynamic flow equals the optical flow:
\[ \mathbf{F}_{o\ell} = \mathbf{F}_{s\ell} + \mathbf{F}_{d\ell}. \] (1)

Our network operates on a sequence of images \( \{ \mathbf{I}_t \}_{t=0}^N \). As new frames are processed, our network iteratively updates not only the camera poses \( \{ \mathbf{G}_t \}_{t=0}^N \in SE(3) \) and inverse depths \( \{ \mathbf{d}_t \}_{t=0}^N \in \mathbb{R}^{H \times W} \), but also the dynamic flows \( \{ \mathbf{F}_{d\ell} \}_{t=0}^N \in \mathbb{R}^{H \times W \times 2} \) and the binary dynamic masks \( \{ \mathbf{M}_{d\ell} \}_{t=0}^N \in \mathbb{R}^{H \times W \times 2} \). We let 0 indicate dynamic while 1 indicate static in \( \mathbf{M}_{d\ell} \).

**Dynamic Update Module**

Fig. 2 demonstrates the dynamic update module of our method, which contains a 3x3 ConvGRU with a hidden state \( \mathbf{h} \). Different from the normal update module, which only works on the static flow residual, our dynamic update module works on both static and dynamic flow fields, respectively. For dynamic flow field, we integrate it with the static flow to compute the optical flow. This combined flow is then fed into the flow encoder as a new optimization term for the subsequent iteration. During each iteration, the update module generates a pose increment, depth increment, dynamic mask increment, and dynamic flow. The pose increment is applied to the current pose through retraction on the SE3 manifold:
\[ \mathbf{G}^{(k+1)} = \text{Exp}(\Delta \mathbf{\xi}^{(k)}) \circ \mathbf{G}^{(k)}. \] (2)

While the depth and the dynamic mask increment are added to the current depth and dynamic mask, respectively:
\[ \Xi^{(k+1)} = \Delta \Xi^{(k)} + \Xi, \quad \Xi \in \{ \mathbf{d}, \mathbf{M}_{d} \}. \] (3)

And \( \mathbf{F}_{d}^{(k+1)} \) is directly assigned a new value in each iteration. With the updated static flow \( \mathbf{F}_{s}^{(k+1)} \) transformed from \( \mathbf{G}^{(k+1)} \) and \( \mathbf{d}^{(k+1)} \), the final optical flow can be computed using Eq. 1.

In summary, our dynamic update module produces a sequence of poses, depths, dynamic masks, dynamic flows, and complete optical flows with the expectation of converging to an optimal point, such as \( \{ \mathbf{G}^{(k)} \} \rightarrow \mathbf{G}^*, \{ \mathbf{d}^{(k)} \} \rightarrow \mathbf{d}^*, \{ \mathbf{M}_{d}^{(k)} \} \rightarrow \mathbf{M}_{d}^*, \{ \mathbf{F}_{d}^{(k)} \} \rightarrow \mathbf{F}_{d}^*, \{ \mathbf{F}_{o}^{(k)} \} \rightarrow \mathbf{F}_{o}^* \).

**Dynamic Update Process**

Our dynamic update module produces several outputs: (1) a static flow residual field \( \mathbf{r}_{s\ell ij} \in \mathbb{R}^{H \times W \times 2} \), (2) an updated dynamic flow field \( \mathbf{F}_{d\ell ij} \in \mathbb{R}^{H \times W \times 2} \), (3) a correlation confidence map \( \mathbf{w}_{ij} \in \mathbb{R}^{H \times W \times 2} \), (4) an updated dynamic mask increment field \( \Delta \mathbf{M}_{d\ell ij} \in \mathbb{R}^{H \times W \times 2} \). For initialization, the dynamic mask \( \mathbf{M}_{d\ell ij} \) and the initial dynamic flow \( \mathbf{F}_{d\ell ij} \) are both set to zeros. The residual \( \mathbf{r}_{s\ell ij} \) is used to correct errors in the dense correspondence fields, which can be expressed as \( \mathbf{p}_{s\ell ij} = \mathbf{r}_{s\ell ij} + \mathbf{p}_{s\ell ij} \). The maps predicted by the module are in low resolution. To obtain the original resolution maps, we follow the mask upsample method mentioned in (Teed and Deng 2021a) to get better upsample results.

**Dense Bundle Adjustment Layer**

After we get the static flow residual field, we optimize the poses and depth maps using a dense bundle adjustment layer (Teed and Deng 2021a). Its cost function is defined as follows:
\[ \mathbf{E}(\mathbf{G}', \mathbf{d}') = \sum_{(i,j) \in \mathcal{E}} \left\| \mathbf{p}_{s\ell ij} - \Pi_c (\mathbf{G}_{ij} \circ \Pi_c^{-1}(\mathbf{p}_i, \mathbf{d}_j)) \right\|^2_\Sigma_{ij}, \] (4)
\[ \Sigma_{ij} = \text{diag} \mathbf{w}_{dij}, \] (5)
\[ \mathbf{w}_{dij} = \text{sigmoid}(\mathbf{w}_{ij} - (1 - \mathbf{M}_{dij}) \cdot \eta), \] (6)

where \( \eta \) is set as 10. \( \parallel \cdot \parallel_\Sigma \) is the Mahalanobis distance, which weights the error term according to the modified confidence \( \mathbf{w}_{dij} \).

To supervise the geometric predictions in a self-supervised scheme, we introduce a photometric reprojection loss (Godard et al. 2020) to guide the network’s optimization. Given the predicted pose \( \mathbf{G}_{ij} \) and the predicted depth \( \mathbf{d}_ij \), we can get the corresponding coordinates of pixels in image \( I_i \) in image \( I_j \). We then use bi-linear sampling to sample the image \( I_j \), getting a new-sampled image \( I_{j\rightarrow i} \):
\[ I_{j\rightarrow i} = I_j \left( \Pi_c (\mathbf{G}_{ij} \circ \Pi_c^{-1}(\mathbf{p}_i, \mathbf{d}_j)) \right). \] (7)

Then we can use the photometric loss on source image \( I_i \) and new image \( I_{j\rightarrow i} \):
\[ \mathcal{L}_{\text{geo-ph}} = \frac{1}{N} \sum_{ij} \text{pe} (I_i, I_{j\rightarrow i}). \] (8)

We leverage \( L_1 \) loss and SSIM (Zhou et al. 2004) loss to form our geometry photometric loss with \( \alpha = 0.85; \)
\[ \text{pe} (I_a, I_b) = \frac{\alpha}{2} (1 - \text{SSIM} (I_a, I_b)) + (1 - \alpha) \parallel I_a - I_b \parallel_1. \] (9)

**DINO Mask Guidance for Geometry**

In our self-supervised training scheme, directly using the dual-flow representation in the photometric loss may lead to pixel mismatches due to object motion. Relying solely on optical flow warping may cause the convergence of two different flows, compromising the network’s ability to decompose the scene. Therefore, a robust prior is needed during training to help the network achieve an initial scene decomposition. Assuming that most dynamic objects in the scene are foreground entities, we use the foreground regions as a prior. We adopt the method proposed by (Amir et al. 2021), utilizing the high-quality and generalizable DINO features (Caron et al. 2021) to cluster the foreground parts \( \mathbf{M}_{d\text{dino}} \) of the scene images. This prior is used to filter out potential dynamic pixel
matches, enhancing our model’s training process. So the final geometry photometric loss function is:

$$ L_{geo,ph} = \frac{1}{N'} \sum_{ij} pe(I_i, I_{j\rightarrow i}) \cdot M^dino_{ij}, \quad (10) $$

where $N'$ means the count of pixels whose $M^dino$ value is 1. Tab. 5 shows the guidance strategy helps filter out the ambiguous matches, obtaining better results.

**Optical Flow Photometric Loss** The geometric photometric loss is used to supervise the static flow caused by camera motion. For the remaining part, we introduce an optical flow photometric loss to supervise the complete scene motion, including both camera and object motion. Through the update module, the optical flow results $F_{ij}$ are derived by combining static and dynamic flows. Similar to $L_{geo,ph}$, we use $F_{ij}$ to generate corresponding coordinates between images:

$$ I_{j\rightarrow i} = I_j(F_{ij} + p_{ij}). \quad (11) $$

Using bi-linear sampling to sample from the source image, we evaluate their photometric errors:

$$ L_{flow,ph} = \sum_{ij} pe(I_i, I_{j\rightarrow i}), \quad (12) $$

where the $pe$ function here is just $L_1$ loss:

$$ pe(I_i, I_j) = \|I_i - I_j\|_1. \quad (13) $$

**DINO Guided Mask Loss** The mask $M^dino_{ij}$ serves as a reliable prior for identifying potential dynamic regions during the early stages, when the network’s predictions may lack precision. Consequently, we directly use it to supervise our predicted masks using a cross-entropy classification loss (Jadon 2020):

$$ L_{dino,mask} = -\frac{1}{|N|} \sum_{p_i \in N} M^dino_{ij} \log \hat{M}_i + (1 - M^dino_{ij}) \log (1 - \hat{M}_i), \quad (14) $$

where $\hat{M}_i$ represents the predicted mask.

**Artificial Mask Loss** The mask $M^dino_{ij}$ provides a potential representation of dynamic regions, though it is not yet accurate enough. To enhance this, we adopt a method similar to (Baur et al. 2021), using the dual-flow representation to artificially construct an additional prior mask that serves as both a supplement and a form of regularization. With the camera poses, depths, and optical flows we have already obtained, we can infer the target coordinate of pixel $p$ using the following equations:

$$ p_{cam} = \Pi_c(G_{ij} \circ \Pi_c^{-1}(p_i, \hat{d}_i)), p_{flow} = p_i + \hat{F}_{ij}, \quad (15) $$

where $p_{cam}$ is the target coordinate calculated by projection, $p_{flow}$ is the target coordinate calculated by optical flow. We then use the difference between these two coordinates to create our artificial mask prior, where sufficiently large difference indicates dynamic regions:

$$ M^art_i = \|p_{cam} - p_{flow}\|_2 \leq \mu. \quad (16) $$

where $\mu$ is set as 0.5. This artificial mask prior has the same format as $M^dino_{ij}$, so our final loss function should be:

$$ L_{art,mask} = -\frac{1}{|N|} \sum_{p_i \in N} M^art_i \log \hat{M}_i + (1 - M^art_i) \log (1 - \hat{M}_i). \quad (17) $$

**Complete Loss Function** Our complete loss function is:

$$ L_{self-sup} = \lambda_1 L_{geo,ph} + \lambda_2 L_{flow,ph} + \lambda_3 L_{dino,mask} + \lambda_4 L_{art,mask}, \quad (18) $$

where $\lambda_1 = 100$, $\lambda_2 = 5$, $\lambda_3 = 0.05$, and $\lambda_4 = 0.05$. Since the network has several update iterations, we use $\gamma = 0.9$ to apply the loss to the output of each iteration with exponentially increasing weights.

**Implementation Details**

We implement $D^3$FlowSLAM in PyTorch and use the LiTorch extension (Teed and Deng 2021b) to perform back-propagation in the tangent space of all group elements. In the ablation study, we train our model on the Virtual KITTI2 dataset (Cabon, Murray, and Humenberger 2020) with 2 RTX-3090 GPUs for 80,000 steps, which takes about 2.5 days. In the full training, we use the TartanAir dataset (Wang et al. 2020) and the PointOdyssey dataset (Zheng et al. 2023) together. It takes 9 days for 300k steps on 4 RTX-3090 GPUs. We use Adam (Kingma and Ba 2014) optimizer with a learning rate of 0.00025.

During training, we use a 6-frame video sequence as one batch data. In temporal dimension, we randomly select frames to add to the sequence with a specific step size. Both the step size and the overall span of the sequence are constrained. For the first frame pair in each batch, we use the 2D-2D epipolar constraint function provided by OpenCV (Bradski 2000) to directly initialize the pose transformation between the first and second frame images. This initialization step enhances training effectiveness and accelerates network convergence. During evaluation, the priors provided by the DINO model are no longer needed. We keep the same system settings in (Teed and Deng 2021a), achieving 10 fps at a resolution $240 \times 808$ and 15 fps at $240 \times 320$. Other details can be found in our appendix.

Figure 3: Reconstruction visualizations of our method. Our method can generalize to different datasets.
### Table 1: Dynamic SLAM Results on KITTI(K) & Virtual KITTI2(VK) Datasets with Metric: ATE[m]. Bold stands for best results. * means the results are generated by running the official pretrained model in our environment to ensure evaluation consistency. X means the system has failed here. - means lack of results.

| Method                  | K09   | K10   | VK01  | VK02  | VK06  | VK18  | VK20  | Avg   |
|-------------------------|-------|-------|-------|-------|-------|-------|-------|-------|
| Sup                     |       |       |       |       |       |       |       |       |
| DynaSLAM* (Bescos et al. 2018) | 18.910 | 7.519 | 27.830 | X     | X     | 2.807 | -     | -     |
| DROID-SLAM* (Teed and Deng 2021a) | 47.053 | 11.001 | 2.259  | 0.049 | 0.136 | 1.170 | 6.998 | 9.816 |
| PVO (Ye et al. 2023) | 14.650 | 8.660 | 0.369  | 0.055 | 0.113 | 0.822 | 3.079 | 3.964 |
| Trad                    |       |       |       |       |       |       |       |       |
| DSO (Engel, Koltun, and Cremers 2017a) | 28.100 | 24.000 | -      | -     | -     | -     | -     | -     |
| ORB-SLAM (Mur-Artal, Montiel, and Tardos 2015) | 6.620  | 8.800  | -      | -     | -     | -     | -     | -     |
| S-Sup                   |       |       |       |       |       |       |       |       |
| Dynamo-Depth (Sun and Hariharan 2024) | 130.536 | 62.417 | 33.516 | 1.232 | 2.035 | 10.761 | 22.058 | 37.508 |
| Ours                    | 10.608 | 3.984 | 1.151  | 0.109 | 0.093 | 0.750 | 3.269 | 2.852 |

### Table 2: Dynamic SLAM Results on TUM Dynamic Sequences with Metric: ATE[m]. The rest references are DVO SLAM (Kerl, Sturm, and Cremers 2013), ORB-SLAM2 (Mur-Artal and Tardós 2017) and PointCorr (Dai et al. 2020).

| Method                  | fr2/d-person | fr3/s-static | fr3/s-xyz | fr3/s-rpy | fr3/s-half | fr3/w-static | fr3/w-xyz | fr3/w-rpy | fr3/w-half | Avg   |
|-------------------------|---------------|--------------|-----------|-----------|------------|--------------|-----------|-----------|------------|-------|
| Sup                     | 0.017         | 0.007        | 0.016     | 0.029     | 0.022      | 0.016        | 0.019     | 0.059     | 0.312      | 0.055 |
| PVO                     | 0.013         | 0.006        | 0.014     | 0.027     | 0.022      | 0.007        | 0.018     | 0.056     | 0.221      | 0.043 |
| Point-Corr              | 0.008         | 0.010        | 0.009     | 0.023     | 0.024      | 0.011        | 0.087     | 0.161     | 0.035      | 0.041 |
| Trad                    | 0.104         | 0.012        | 0.242     | 0.176     | 0.220      | 0.752        | 1.383     | 1.292     | 1.014      | 0.688 |
| ORB-SLAM2               | 0.006         | 0.008        | 0.010     | 0.025     | 0.025      | 0.408        | 0.722     | 0.805     | 0.723      | 0.303 |
| S-Sup                   | 1.173         | 0.015        | 0.299     | 0.051     | 0.379      | 0.018        | 0.283     | 0.153     | 0.458      | 0.314 |
| Dynamo-Depth (Sun and Hariharan 2024) | 10.608 | 3.984 | 1.151   | 0.109   | 0.093   | 0.750 | 3.269 | 2.852 |
| Ours                    | 0.069         | 0.007        | 0.018     | 0.039     | 0.117      | 0.008        | 0.112     | 0.143     | 0.114      | 0.070 |

### Experiments

We train our model in a self-supervised scheme and test our model on different datasets. We use absolute trajectory error (ATE) (Sturm et al. 2012) to evaluate the accuracy of the estimated camera trajectories. We compare our method with traditional methods (Trad), learning-based supervised methods (Sup), and the latest self-supervised methods (S-Sup) similar to ours. Specifically, we choose Dynamo-Depth (Sun and Hariharan 2024) because it is the best method among existing self-supervised approaches for providing pose estimation in dynamic scenes.

### Datasets

We validate the effectiveness of our method in highly dynamic scenes like Virtual KITTI2 (Cabon, Murray, and Humenberger 2020) in the ablation study. Virtual KITTI2 is derived from the KITTI benchmark (Geiger et al. 2013) and consists of 5 sequences augmented with various weather conditions. We use the clone split for training and the 15-degree split for testing.

To get our final weight, we use larger datasets like TartanAir (Wang et al. 2020) and PointOdyssey (Zheng et al. 2023) for training. TartanAir is a large synthetic static dataset that includes a rich variety of simulated images from both indoor and outdoor scenes. As a supplement, we include the PointOdyssey dataset, which is another large synthetic dataset containing a wealth of dynamic scene data. We test our method on various dynamic datasets such as Virtual KITTI2, KITTI, dynamic sequences from TUM-RGBD (Schubert et al. 2018), and traditional SLAM datasets including static scenes from TUM-RGBD, EuroC (Burri et al. 2016), and TartanAir-Test (Wang et al. 2020). The visualizations in Fig. 3 show that our model runs well in different datasets. For the final evaluation on different datasets, we use the self-supervised nature to perform simple finetuning on our final weight and Dynamo-Depth’s official weight with specific image sequences from these datasets. Details can be found in our appendix.

### Dynamic SLAM

In dynamic settings, we test on sequences 09 and 10 from the KITTI (K) dataset and all sequences from the Virtual KITTI2 (VK) dataset. ATE results are shown in Tab. 1. We also test on TUM-RGBD dynamic sequences, as shown in Tab. 2. Our method significantly outperforms the best existing self-supervised methods, especially in challenging dynamic scenes like K and VK. While Dynamo-Depth’s estimation results are subpar in these scenarios, our method still delivers accurate estimations. Compared to traditional or supervised methods, our method also achieves comparable or better results. We achieve an average ATE of 2.852m on VK+K and 0.07m on TUM-RGBD dynamic, which con-
### Monocular SLAM

In monocular settings, we test our method on TartanAir-Test, EuRoC, and TUM-RGBD dataset. Results for TUM-RGBD can be found in our appendix. Tab. 3 and Tab. 4 show that in static scenes, our method also substantially outperforms other self-supervised methods. Compared to existing supervised methods and traditional methods, our results remain competitive. Specifically, we achieve an average ATE of 0.79m on TartanAir-Test, 0.561m on EuRoC in the monocular setting, and 0.127m on TUM-RGBD static sequences.

#### Ablation Study

We conduct an ablation study to verify the effectiveness of our dual-flow representation and DINO Guidance. The use of the Virtual KITTI2 dataset for both training and testing in the ablation study. The experimental results are detailed in Tab. 5. Specifically, SF means only using \( L_{\text{geo, ph}} \), DF means using \( L_{\text{flow, ph}} \) and \( L_{\text{geo, ph}} \), and DINO means adding \( L_{\text{dino, mask}} \). The results show that the dual-flow (DF) representation outperforms the rough single-flow (SF) approach. Additionally, DINO Guidance enhances the pose estimation accuracy and greatly improves our model’s ability to decompose dynamic scenes. It provides a stronger prior and reduces the impact of pixel matching errors. Fig. 5 offers a more intuitive demonstration of the improvements brought by DINO Guidance. Additionally, compared to the results in Tab. 1, our model achieves comparable or better results after full training and finetuning. Additionally, the results from Tab. 1 and 5 demonstrate that our model, when trained on large datasets and then finetuned, achieves performance comparable to training directly on specific datasets.

#### Conclusions

In D^3FlowSLAM, we propose a dual-flow representation that decomposes optical flow into static flow and dynamic flow. Based on this, our dynamic update module simultaneously updates these two flow fields, enabling geometric information retrieval and scene decomposition in both static and dynamic environments. Additionally, we design a self-supervised scheme that enables label-free training and significantly outperforms existing self-supervised methods. Our limitations include the need for a GPU and a lim-

| Method                  | MH000 | MH001 | MH002 | MH003 | MH004 | MH005 | MH006 | MH007 | Avg       |
|-------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-----------|
| DeepV2D (Teed and Deng 2018) | 6.15  | 2.12  | 4.54  | 3.89  | 2.71  | 11.55 | 5.53  | 3.76  | 5.03      |
| Sup                     | 4.88  | 0.26  | 2.00  | 0.94  | 1.07  | 3.19  | 1.00  | 2.04  | 1.92      |
| DROID-SLAM* (Teed and Deng 2021a) | 0.04  | 0.69  | 0.03  | 0.02  | 3.73  | 1.29  | 0.38  | 0.07  | 0.78      |
| TartanVO (Wang, Hu, and Scherer 2021) | 15.44 | 2.92  | 13.51 | 8.18  | 2.59  | 21.91 | 11.70 | 25.88 | 12.77     |
| DSO (Engel, Koltun, and Cremers 2017b) | 9.92  | 0.35  | 7.96  | 3.46  | -     | 12.58 | 8.42  | 7.50  | -         |
| S-Sup Dynamo-Depth (Sun and Hariharan 2024) | 33.36 | 7.67  | 15.89 | 10.13 | 9.39  | 19.46 | 16.94 | 15.08 | 15.99     |
| Ours                    | 0.83  | 0.11  | 0.19  | 0.36  | 2.41  | 1.62  | 0.19  | 0.58  | 0.79      |

**Table 3: Monocular SLAM Results on TartanAir Monocular Benchmark with Metric: ATE[m].**

| Method                  | MH001 | MH002 | MH003 | MH004 | MH005 | V101 | V102 | V103 | V201 | V202 | V203 | Avg     |
|-------------------------|-------|-------|-------|-------|-------|------|------|------|------|------|------|---------|
| DeepFactors (Czarnowski et al. 2020) | 1.587 | 1.479 | 3.139 | 5.331 | 4.002 | 1.520 | 0.679 | 0.900 | 0.876 | 1.905 | 1.021 | 2.040   |
| DeepV2D (Teed and Deng 2018) | 0.739 | 1.144 | 0.752 | 1.492 | 1.567 | 0.981 | 0.801 | 1.570 | 0.290 | 2.202 | 2.743 | 1.298   |
| TartanVO (Wang, Hu, and Scherer 2021) | 0.639 | 0.325 | 0.550 | 1.153 | 1.021 | 0.447 | 0.389 | 0.622 | 0.433 | 0.749 | 1.152 | 0.680   |
| D3VO + DSO (Yang et al. 2020) | -     | -     | -     | 0.09  | -     | 0.09  | -     | 0.11  | -     | 0.05  | 0.19  | -       |
| DROID-SLAM* (Teed and Deng 2021a) | 0.013 | 0.014 | 0.022 | 0.043 | 0.043 | 0.037 | 0.012 | 0.020 | 0.017 | 0.013 | 0.042 | 0.022   |
| DSO (Engel, Koltun, and Cremers 2017b) | 0.138 | 0.072 | 0.039 | 0.036 | 0.055 | 0.057 | 0.067 | 0.095 | 0.059 | 0.076 | 0.056 | 0.057   |
| SVM (Forster et al. 2016) | 0.009 | 0.009 | 0.009 | 0.009 | 0.009 | 0.009 | 0.009 | 0.009 | 0.009 | 0.009 | 0.009 | 0.009   |
| DSM (Zubizarreta, Aguinaga, and Montiel 2020) | 0.016 | 0.027 | 0.028 | 0.138 | 0.072 | 0.033 | 0.015 | 0.033 | 0.023 | 0.029 | X     | -       |
| ORB-SLAM3 (Campos et al. 2020) | 0.116 | 0.184 | 0.210 | 0.243 | 0.775 | 1.762 | 1.746 | 1.480 | 0.022 | 0.070 | 0.210 | X       |
| S-Sup Dynamo-Depth (Sun and Hariharan 2024) | 2.598 | 3.773 | 4.130 | 6.298 | 6.460 | 1.762 | 1.746 | 1.480 | 2.017 | 2.054 | 1.908 | 3.198   |
| Ours                    | 0.793 | 0.029 | 0.121 | 0.382 | 3.083 | 0.046 | 0.109 | 0.197 | 0.005 | 0.023 | 0.029 | X       |

**Table 4: Monocular SLAM Results on EuRoC Dataset with Metric: ATE[m].**

**Table 5: Ablation Study on Virtual KITTI2(VK) Dataset.** SF means single flow, DF means dual flow, and DINO means DINO Guidance.

| Method                  | Tek V01 | Tek V02 | Tek V06 | Tek V18 | Tek V20 |
|-------------------------|---------|---------|---------|---------|---------|
| DROID-SLAM (Sup)        | 1.091   | 0.025   | 0.113   | 1.156   | 8.285   |
| Ours (SF)               | 3.281   | 0.194   | 0.093   | 1.183   | 10.259  |
| Ours (DF)               | 4.045   | 0.185   | 0.095   | 2.141   | 8.782   |
| Ours (DF, DINO)         | 0.793   | 0.029   | 0.121   | 0.382   | 3.083   |

**Figure 5: Ablation for DINO Guidance.** From left to right: Input image, prediction with DINO, and prediction without DINO. Colorful masks indicate dynamic parts.
further increasing the model’s prediction accuracy. In future work, we plan to enhance the computational efficiency of our model and its training scheme to improve adaptability and robustness, while also further increasing the model’s prediction accuracy.

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D³FlowSLAM: Self-Supervised Dynamic SLAM with Flow Motion Decomposition and DINO Guidance

Supplementary Material

In this appendix, we will discuss some details not elaborated in the main paper, along with additional experimental results and visualizations.

**Preliminaries: DROID-SLAM**

DROID-SLAM (Teed and Deng 2021a) operates on a sequence of images \(\{I_t\}_{t=0}^{N}\) and maintains two state variables: camera pose \(G_t \in SE(3)\) and inverse depth \(d_t \in \mathbb{R}_{+}^{H \times W}\) for each image \(I_t\), which are iteratively updated as new frames are processed. A frame graph \(G = (\mathcal{V}, \mathcal{E})\) is used to represent co-visibility between frames, where the nodes correspond to input images, and an edge \((i, j) \in \mathcal{E}\) indicates that images \(I_i\) and \(I_j\) have overlapping views.

**Feature Extraction and Correlation**

Following RAFT (Teed and Deng 2020), the input images are first processed by the feature extraction module, after which the relationship between the two images is computed.

**Feature Extraction.** First, an image encoder with six residual blocks and three downsampling layers processes each image, producing a dense feature map at \(1/8\) of the original resolution. These feature maps from input image pairs are then used for constructing the correlation volume.

**Correlation Pyramid.** For each edge \((i, j) \in \mathcal{E}\) in the frame graph \(G\), DROID-SLAM computes the correlation volume \(C_{ij}\) as the dot product of feature vector pairs taken from \(f_0(I_i)_{u_i,v_i}\) and \(f_0(I_j)_{u_j,v_j}\):

\[
C_{ij}^{u_i,v_i,u_j,v_j} = \langle f_0(I_i)_{u_i,v_i}, f_0(I_j)_{u_j,v_j} \rangle,
\]

where \(u_i,v_i,u_j,v_j\) represent the pixel coordinates for image \(I_i, I_j\) respectively, and \(<, >\) stands for the dot product. The last two dimensions of the correlation volume are fed to the average pooling layers with four different kernel sizes \((1,2,4,8)\), forming a 4-level correlation pyramid (Teed and Deng 2020).

**Correlation Lookup.** RAFT defines a correlation lookup operator that uses a coordinate grid with radius \(r\) to index the correlation volume \(L_r: \mathbb{R}^{H \times W \times H \times W} \times \mathbb{R}^{H \times W \times 2} \rightarrow \mathbb{R}^{H \times W \times (r+1)^2}\). This operator takes an \(H \times W\) grid of optical flow coordinates as input and retrieves values from the correlation volume using bi-linear interpolation. These values are then concatenated to compute the final feature vector. The lookup function is applied to each correlation volume in the pyramid.

**Update Module**

DROID-SLAM introduces an update operator where a \(3 \times 3\) ConvGRU is used to update the hidden state \(h\), the camera pose \(G\) and depth \(d\). The final pose and depth are obtained by applying incremental updates \(\Delta \xi^{(k)}\) and \(\Delta d^{(k)}\) to the current estimates through retraction on the \(SE(3)\) manifold and vector addition, respectively:

\[
G^{(k+1)} = \text{Exp}((\Delta \xi^{(k)}) \circ G^{(k)}), \quad d^{(k+1)} = \Delta d^{(k)} + d^{(k)}.
\]

The update operator iteratively produces a sequence of poses and depths with the goal of converging to a fixed point:

\[
\{G^{(k)}\} \rightarrow G^*,\{d^{(k)}\} \rightarrow d^*.
\]

**DINO Guidance**

For DINO Guidance, we have also considered using features from the DINOv2 (Oquab et al. 2023) model. However, our basic requirement for foreground masks is precision, with finer edges for foreground objects being preferable. Despite DINOv2 providing higher-quality features compared to DINO (Caron et al. 2021), its lower resolution feature maps lead to poorer mask quality when using clustering methods (Amir et al. 2021), resulting in less detailed masks. Based on this, we ultimately choose DINO for DINO Guidance.

**Implementation Details**

**Training Initialization**

To improve training efficiency, we preprocess all training data using functions provided by OpenCV (Bradski 2000) to select image pairs. We assume that the training data is temporally continuous. For any given frame, we consider the \(N\) adjacent frames as the selection window. We first filter out frames in this window that can be triangulated with the current frame. Then, we use OpenCV to compute sparse optical flow from the remaining matched points to the current frame. Frames with an average optical flow outside a specified range are discarded. The remaining frames are considered candidates, and during training, we randomly select one of these frames to pair with the current frame.
Table 1: Monocular SLAM Results on TUM-RGBD Dataset with Metric: ATE[m]. Bold stands for best results. * means the results are generated by running the official pretrained model in our environment to ensure evaluation consistency. X means the system has failed here. - means lack of results.

| Method | 360 | desk | desk2 | floor | plant | room | rpy | teddy | xyz | Avg |
|--------|-----|------|-------|-------|-------|------|-----|-------|-----|-----|
| DeepV2D (Teed and Deng 2018) | 0.243 | 0.166 | 0.379 | 1.653 | 0.203 | 0.246 | 0.105 | 0.316 | 0.064 | 0.375 |
| DeepFactors (Czarnowski et al. 2020) | 0.159 | 0.170 | 0.253 | 0.169 | 0.305 | 0.364 | 0.043 | 0.601 | 0.035 | 0.233 |
| Sup | | | | | | | | | | |
| TartanVO (Wang, Hu, and Scherer 2021) | 0.178 | 0.125 | 0.122 | 0.349 | 0.297 | 0.333 | 0.049 | 0.339 | 0.062 | 0.206 |
| DeepTAM (Zhou, Ummenhofer, and Brox 2018) | 0.111 | 0.053 | 0.103 | 0.206 | 0.064 | 0.239 | 0.093 | 0.144 | 0.036 | 0.116 |
| DROID-SLAM* (Teed and Deng 2021a) | 0.111 | 0.018 | 0.042 | 0.021 | 0.016 | 0.049 | 0.026 | 0.048 | 0.012 | 0.038 |
| Trad | | | | | | | | | | |
| ORB-SLAM3 (Campos et al. 2020) | X | 0.017 | 0.210 | X | 0.034 | X | X | X | 0.009 | - |
| S-Sup | Dynamo-Depth (Sun and Hariharan 2024) | Ours | 0.177 | 0.838 | 0.930 | 0.705 | 0.663 | 0.987 | 0.048 | 0.868 | 0.182 | 0.711 |
| | Ours | 0.180 | 0.019 | 0.138 | 0.344 | 0.019 | 0.323 | 0.044 | 0.062 | 0.018 | 0.127 |

Table 2: Stereo SLAM results on EuRoC Dataset with Metric: ATE[m].

| Method | MH01 | MH02 | MH03 | MH04 | MH05 | V101 | V102 | V103 | V201 | V202 | V203 | Avg |
|--------|------|------|------|------|------|------|------|------|------|------|------|-----|
| Sup | | | | | | | | | | | | |
| D3VO + DSO (Yang et al. 2020) | - | - | 0.08 | - | 0.09 | - | - | 0.11 | - | 0.05 | - | - |
| DROID-SLAM* (Teed and Deng 2021a) | 0.015 | 0.013 | 0.035 | 0.048 | 0.040 | 0.037 | 0.011 | 0.020 | 0.018 | 0.015 | 0.017 | 0.024 |
| Trad | | | | | | | | | | | | |
| VINS-Fusion (Qin and Shen 2018) | 0.540 | 0.460 | 0.330 | 0.780 | 0.500 | 0.550 | 0.230 | - | 0.230 | 0.200 | - | - |
| SVO (Forster et al. 2016) | 0.040 | 0.070 | 0.270 | 0.170 | 0.120 | 0.040 | 0.040 | 0.070 | 0.050 | 0.090 | 0.790 | 0.159 |
| ORB-SLAM3 (Campos et al. 2020) | 0.029 | 0.019 | 0.024 | 0.085 | 0.052 | 0.035 | 0.025 | 0.061 | 0.041 | 0.028 | 0.521 | 0.084 |
| S-Sup | Dynamo-Depth (Mono) (Sun and Hariharan 2024) | Ours | 4.26 | 3.77 | 3.43 | 6.30 | 6.46 | 1.76 | 1.75 | 1.48 | 2.02 | 2.05 | 1.91 | 3.16 |
| | Ours | 0.164 | 0.140 | 0.202 | 0.299 | 0.257 | 0.076 | 0.054 | 0.116 | 0.044 | 0.097 | 0.246 | 0.154 |

**SLAM System Details**

We follow similar system settings as described in (Teed and Deng 2021a). During initialization, D3FlowSLAM continuously receives new frames until a total of 12 are collected. It constructs frame graphs for these frames and uses our dynamic update module to compute their initial pose and inverse depth maps. In the front-end, when a new frame arrives, the system constructs a temporary graph with the new frame and its three nearest neighbors. Within this graph, the hidden states of the new frame, such as pose and inverse depth, are optimized. In the back-end, the system creates a new graph containing all preserved keyframes. Edges between keyframes are generated according to specific rules to eliminate redundancy. The dynamic update module is then used to optimize the entire graph for final poses and depths.

**Experiments**

**More SLAM Results**

The detailed results for TUM-RGBD static sequences are presented in Tab. 1. Our method outperforms the latest self-supervised method and matches the performance of supervised and traditional methods, achieving an average ATE of 0.127m. We also test our system in the stereo input mode. We test our method on TartanAir-Test stereo dataset and EuRoC stereo dataset. The self-supervised method (Sun and Hariharan 2024) remains the same.

**Finetuning Settings**

As mentioned in the main paper, we finetune our pretrained model, which was initially trained on the full TartanAir and PointOdyssey datasets, using the Virtual KITTI2, KITTI, TartanAir-Test, and EuRoC datasets. Since our method is self-supervised, we only require images from these sequences for finetuning, with a learning rate of 0.0001. For Virtual KITTI2, we use the clone split of all scenes. For KITTI, we use Seq 00, 01, 07, 08. For TartanAir-MonoTest, we use ME003, MH006. For EuRoC, we use right(left for evaluation) camera images for Seq MH01, MH02, V101, V201. The finetuning images for Dynamo-Depth (Sun and Hariharan 2024) remain the same.

Tab. 4 shows the results for part of sequences from the EuRoC and TartanAir-Test datasets before and after finetuning. It shows that the finetuning significantly enhances performance on sequences where the initial results were suboptimal. This underscores our model’s ability to adapt to new datasets and environments using a self-supervised scheme.

**Trajectory Visualization**

We present some of our trajectory visualization results to intuitively demonstrate the effectiveness of our trajectory estimation. In Fig. 3 we show the trajectories in the Virtual KITTI2 dataset. In Fig. 4 we show the trajectories in the KITTI dataset. As seen in these figures, our trajectories in these dynamic scenes are closer to the ground truth trajectories compared to other approaches.

**AR Applications**

We conduct extensive experiments on AR applications in dynamic scenes to demonstrate the robustness of our method.
Table 3: Stereo SLAM results on TartanAir Stereo Benchmark with Metric: ATE[m].

| Method | SH000 | SH001 | SH002 | SH003 | SH004 | SH005 | SH006 | SH007 | Avg |
|--------|-------|-------|-------|-------|-------|-------|-------|-------|-----|
| Sup TartanVO (Wang, Hu, and Scherer 2021) | 2.52 | 1.61 | 3.65 | 0.29 | 3.36 | 4.74 | 3.72 | 3.06 | 2.87 |
| | DROID-SLAM* (Teed and Deng 2021a) | 0.44 | 0.08 | 0.13 | 0.20 | 0.16 | 3.29 | 0.38 | 0.18 | 0.61 |
| Trad ORB-SLAM2 (Mur-Artal and Tardós 2017) | 0.05 | 6.67 | X | X | X | X | 0.10 | X | - |
| S-Sup Dynamo-Depth (Mono) (Sun and Hariharan 2024) | 37.73 | 31.11 | 14.38 | 11.32 | 14.39 | 29.43 | 46.85 | 24.51 | 26.71 |
| Ours | 0.32 | 1.94 | 1.26 | 0.15 | 0.29 | 6.72 | 0.33 | 0.08 | 1.39 |

Figure 2: AR Application. We augment the original video with a virtual tree and a car. From left to right and from top to down: Ground-Truth, D³FlowSLAM, DROID-SLAM, Original Image.

Table 4: The Comparison of our method’s results Before and After Finetuning with Metric: ATE[m]. We present the evaluation ATE results for part of sequences from the EuRoC and TartanAir-Test datasets. The finetuning operation helps correct some significantly abnormal results.

| Dataset | EuRoC | TartanAir-Test |
|---------|-------|----------------|
| Method | MH02 | MH03 | V101 | V201 | MH000 | MH006 |
| Ours (raw) | 0.281 | 1.789 | 1.183 | 1.028 | 1.380 | 24.507 |
| Ours (finetuned) | 0.184 | 0.210 | 0.058 | 0.041 | 0.833 | 0.194 |

In Fig. 2, we augment the original video with virtual elements such as a tree, car, and street lamp. D³FlowSLAM effectively handles dynamic objects in the scene, while other methods, like (Teed and Deng 2021a), show drift, especially in areas highlighted by the red box.

Discussion and Limitations

We propose D³FlowSLAM, a self-supervised approach that significantly outperforms existing self-supervised methods in both dynamic and static scenes. While our method is versatile and robust in dynamic environments, there are areas for improvement. D³FlowSLAM is less effective in certain static scenarios compared to the SOTA supervised methods due to the absence of strong priors like depth and pose during training. To address this, our future work will explore additional supervisory terms or loss functions to enhance self-supervision. We also aim to better integrate powerful self-supervised pretrained models into the entire SLAM system. Our method currently focuses on camera pose estimation, with depth and optical flow results limited to 1/8 of the original image resolution, which is not ideal for tasks requiring precise depth or optical flow. The model also faces GPU memory limitations with ultra-long image sequences and large scenes, and its running speed does not yet meet real-time requirements. Developing a lightweight, high-performance dynamic SLAM system is a key direction for our future research.
Figure 3: **Comparison Trajectory Results of Our Method with DROID-SLAM.** In dynamic sequences like VKITTI2 Sequences 01(left), 18(middle), and 20(right), our method performs better than DROID-SLAM, with better trajectory estimation results.

Figure 4: **Trajectory Comparison between Our Method and DROID-SLAM.** In KITTI sequences 09(Left) and 10(Right), our trajectories are closer to the ground truth.