PanoFlow: Learning 360° Optical Flow for Surrounding Temporal Understanding

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Abstract—Optical flow estimation is a basic task in self-driving and robotics systems, which enables to temporally interpret traffic scenes. Autonomous vehicles clearly benefit from the ultra-wide Field of View (FoV) offered by 360° panoramic sensors. However, due to the unique imaging process of panoramic cameras, models designed for pinhole images do not directly generalize satisfactorily to 360° panoramic images. In this paper, we put forward a novel network framework—PANOFLOW, to learn optical flow for panoramic images. To overcome the distortions introduced by equirectangular projection in panoramic transformation, we design a Flow Distortion Augmentation (FDA) method, which contains radial flow distortion (FDA-R) or equirectangular flow distortion (FDA-E). We further look into the definition and properties of cyclic optical flow for panoramic videos, and hereby propose a Cyclic Flow Estimation (CFE) method by leveraging the cyclicity of spherical images to infer 360° optical flow and converting large displacement to relatively small displacement. PanoFlow is applicable to any existing flow estimation method and benefits from the progress of narrow-FoV flow estimation. In addition, we create and release a synthetic panoramic dataset FlowScape based on CARLA to facilitate training and quantitative analysis. PanoFlow achieves state-of-the-art performance on the public OmniFlowNet and the fresh established FlowScape benchmarks. Our proposed approach reduces the End-Point-Error (EPE) on FlowScape by 27.3%. On OmniFlowNet, PanoFlow achieves an EPE of 3.17 pixels, a 55.5% error reduction from the best published result (7.12 pixels). We also qualitatively validate our method via an outdoor collection vehicle and a public real-world OmniPhotos dataset, indicating strong potential and robustness for real-world navigation applications. Code and dataset are publicly available at PanoFlow.

Index Terms—Intelligent Vehicles, Scene Parsing, Optical Flow, Panorama, Scene Understanding, Synthetic Dataset.

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Fig. 1. (a) Raw panoramic annular image captured by our mobile perception system, (b)-(c) the proposed panoramic optical flow estimation on real-world surrounding view for 360° seamless scene temporal understanding.

I. INTRODUCTION

O ptical flow estimation is one of the fundamental challenges for autonomous driving [1]–[5]. Flow estimation provides information about the environment and the sensor’s motion, leading to a temporal understanding of the world, which is vital for many robotics and vehicular applications, including scene parsing, image-based navigation, visual odometry, and SLAM [6]–[12]. With the development of spherical cameras [13], panoramic images are now more easily captured for 360° scene perception [14]–[16], and can better be integrated with LiDARs due to the similar projection model [17]. However, learning-based methods have always focused on traditional 2D images produced by pinhole projection model based cameras [18]–[20]. Models designed for a camera with narrow Field-Of-View (FoV) are usually sub-optimal for a comprehensive understanding. Coupling them with 360° LiDARs would also directly lead to inherent and domain adaptation problems [21]. Thus, the ability to infer optical flow of a camera’s complete surrounding has motivated the study of 360° flow estimation.

Unlike classical linear images, panoramic contents often suffer from severe distortions due to the equirectangular projection (ERP) of spherical cameras [22]. An object will
deform to varying degrees at different latitudes in panoramic images, making flow estimation more difficult between the target image and the attended image. Another critical issue lies in the cyclicity of spherical boundaries, which means there is more than one path from the source point to the target point, and usually there is one shorter and one longer path [23]. The two routes together form a great circle on the sphere. In other words, the geometric meanings of the two routes are equivalent. However, traditional learning-based models cannot track pixels moving outside the image boundary, and therefore have no choice but to infer the harder long-distance motion vector, leading to less satisfactory estimation.

To tackle these issues, we introduce a new panoramic flow estimation framework——PANOLOW, to directly estimate dense flow field from panoramic images. We implement PanoFlow on two different state-of-the-art optical flow networks [19], [20] to verify the generality of the proposed framework. We present the first, to the authors’ best knowledge, a Flow Distortion Augmentation (FDA) method, that is built on the insight of the distortion induced by ERP, to enhance robustness against deformations in panoramic images. While distortion augmentation is used in panoramic scene parsing [24], [25], it has not been investigated in optical flow estimation, as optical flow is a 2D vector, which incurs further challenges. Unlike traditional geometric augmentation methods that deal with constant properties, distortion augmentation of optical flow is non-trivial, which has to consider the variation of optical flow because the initial and terminal points of the flow would be distorted to different extent. By projecting participating images (attended- and target images) and flow ground truth onto the distortion field, we improve the model’s ability to generalize to deformed regions.

We put forward two variants of flow distortion augmentation: radial flow distortion (FDA-R) and equirectangular flow distortion (FDA-E). Although FDA-E is consistent with the distortion introduced by general ERP, given the smaller FoV of the pinhole dataset, the number of pixels that really participate in supervision is reduced. We therefore also explore the role of FDA-R in overcoming ERP distortion. We found that although their deformed models are not exactly identical, FDA-R also improves the network’s ability to handle distorted regions. From another distortion-adaptive perspective, we further propose to address the distortion by replacing the first layer of the encoder with a deformable convolution layer [26]. The proposed FDA and the deformable convolution empower the model to handle characteristic panoramic image distortions and robustify flow estimation. As a novel data augmentation method, FDA is a plug-and-play module for any learning-based optical flow network.

Furthermore, we give a standard definition of cyclic optical flow suitable for panorama video stream, analyze the properties of cyclic optical flow and compare it with classical optical flow. We then design a Cyclic Flow Estimation (CFE) method based on the previous insight to leverage the cyclicity of panoramic images, and convert long-distance estimation to a relatively short-distance estimation. CFE well relieves the stress of the model in large displacement estimation, enabling the model to focus on local fine-grained optical flow estimation. CFE is a general optical flow estimation method and thus can benefit from the advances of narrow-FoV flow estimation methods. Interestingly, both quantitative and qualitative results show that, compared to the previous best method [23] which estimates on the cubemap plane and the icosahedral tangent plane iteratively, the CFE method is simple, yet very effective. We also calculate the distribution of the accuracy change with the horizontal FoV before and after using the CFE method, and discover that CFE can significantly improve the optical flow estimation accuracy near the panorama vertical boundary, which is a unique difficulty of panoramic flow estimation.

In addition, to overcome the lack of available panoramic training data and to foster research on 360° understanding, we establish and release a new synthetic panoramic flow estimation benchmark of street scenes——FlowScape. We generate the dataset via the CARLA simulator [27]. FlowScape consists of 6,400 color images, optical flow, and pixel-level semantic ground truth, providing an environment similar to the real world, thanks to dynamic weather, diverse city street scenes, and different types of vehicles. We use this dataset for learning to infer flow from panoramic content. We also analyze the ground-truth quality of existing optical flow datasets [22], [23], [28] when only forward optical flow is given, and determine our evaluation datasets according to the observations.

We conduct extensive quantitative experiments on the established FlowScape benchmark. Compared with the previous best model, the End-Point-Error (EPE) of PanoFlow on this dataset reduces by 27.3%. Further, the EPE of our approach on the public OmniFlowNet dataset [22] is reduced by 55.5% compared with the best published results (3.34 pixels vs. 7.12 pixels). Moreover, a comprehensive set of ablation experiments demonstrates the effectiveness of the proposed FDA and CFE methods. We additionally conduct qualitative analysis on the public real-world OmniPhotos dataset [29] to validate our approach in real-world surrounding perception. To further demonstrate the generalization ability of PanoFlow, we also assemble an outdoor data collection vehicle installed with a Panoramic Annular Lens (PAL) system. As shown in Fig. 1, PanoFlow gives sharp and clean omnidirectional optical flow estimation for real-world surrounding scenes.

In summary, our main contributions are as follows:

- We present a rigorous theoretical definition of 360° optical flow.
- We introduce flow distortion augmentation, a new data augmentation method for optical flow networks, which can help models learn to capture the motion cues even on deformed regions.
- We propose a generic cyclic flow estimation method, which can transform large- to relatively short displacement estimation based on the geometric nature of consecutive panoramas.
- We generate FlowScape, a new publicly available panoramic dataset that consists of diverse synthetic street scenes, providing both pixel-level flow- and semantic ground truth. We also assess ground-truth quality of existing panoramic flow datasets.
- Our entire framework PANOLOW achieves state-of-the-art performance on the established FlowScape benchmark.
and the public OmniFlowNet dataset.

- PanoFlow demonstrates strong generalization ability both on the public real-world OmniPhotos dataset and our captured outdoor panoramic video streams.

II. RELATED WORK

A. Learning-based Optical Flow Estimation

The classical optical flow estimation approaches [30], [31] use variational approaches to minimize energy based on brightness constancy and spatial smoothness. Since the advent of FlowNet [32], some other works based on Convolutional Neural Networks (CNNs) [33]–[44] have appeared. Besides, there are also some self-supervised approaches [45], [46] to learn optical flow with occlusions. Most of these methods are normally designed to work with pinhole cameras capturing a limited imaging angle.

FlowNet [32] first treats optical flow estimation as a learning problem. In order to further improve the accuracy of optical flow, FlowNet2.0 [47] introduces image warping between multiple cascaded FlowNets. Due to the large model size of FlowNet2.0 [47], many methods have been proposed to simultaneously improve the optical flow accuracy and reduce the model size. Among them, PWC-Net [18] combines classical optical flow estimation principles including pyramid processing, image warping, and cost volumes with learning. LiteFlowNet2 [48] draws on the idea of data fidelity and regularization in the classical variational optical flow method. RAFT [19] iteratively update optical flow fields using multi-scale 4D correlation volumes. To better apply optical flow estimation to autonomous driving systems, CSFlow [20] proposes a new optical flow deep network architecture composed of Cross Strip Correlation module (CSC) and Correlation Regression Initialization module (CRI). Moreover, FlowFormer [49] replaces the CNN-based backbone in the RAFT architecture with a transformer-based backbone, which further improves the accuracy of optical flow estimation while increasing the number of parameters by three times. In contrast, PanoFlow is a panoramic optical flow framework that can be adapted to any optical flow network with an encoder-decoder architecture.

B. Optical Flow Estimation beyond the FoV

With the arrival on the market of the increasingly affordable, portable, and accurate panoramic cameras, 360° flow estimation is in urgent need, that can provide a wide-FoV temporal understanding, for which some methods based on deep learning are developed. LiteFlowNet360 [50] is designed as a domain adaptation framework to cope with inherent distortions in 360° videos caused by the sphere-to-plane projection. They employ incremental transformation of convolutional layers in feature pyramid networks to reduce network growth size and computational costs combining data augmentation and self-supervised learning with target-domain 360° videos. OmniFlowNet [22] is built on a CNN model that specializes in perspective images and then applied to omnidirectional ones without training on new datasets, whose convolution operation is unified with equirectangular projection, outperforming the original network. The projection from the 360° image to the ERP image is a nonlinear mapping, and the distortion caused by this will affect the 360° optical flow estimation, thus Yuan et al. [23] propose a 360° optical flow estimation method based on tangent images, including dozens of estimations and refinements on both icosahedron and cubemap panoramas. Overall, the existing learning-based panoramic flow methods adopt a fixed projection paradigm at the model level to deal with ERP distortions. Considering the local bias behavior of CNNs, this will reduce the model’s ability to model potential visual cues and result in unsatisfactory performance. On the other hand, estimation and refinement on tangent planes introduce additional computational costs, leading to limited inference speed. Recently, a concurrent work [51] also explores the 360° optical flow via a siamese representation learning scheme with carefully designed losses and rotational augmentations to adopt existing flow networks. Differing from these works, we tackle image distortions and object deformations that appear across the entire 360° scenes and leverage the cyclicality of consecutive omnidirectional data for enhancing panoramic optical flow estimation.

C. Optical Flow and Panoramic Perception Datasets

Panoramic datasets are needed in a wide variety of application areas, including depth estimation [52]–[54], scene segmentation [55]–[57], and optical flow estimation [22], [23], [28]. Stanford2D3D [58] is a large-scale indoor spaces dataset that consists of both regular and panoramic data with instance-level semantic annotations. The 360D dataset [21] reuses released large-scale 3D datasets and re-purposes them to 360° via rendering for dense depth estimation. PASS [24] presents a panoramic annular semantic segmentation framework with an associated dataset for credible evaluation. DensePASS [59] introduces a dataset with both labeled and unlabeled 360° images for benchmarking panoramic semantic segmentation from a perspective of unsupervised domain adaptation. KITTI-360 [60] is collected with perspective stereo cameras, a pair of fisheye cameras, and a laser scanning unit for enabling 360° perception. WoodScape [61] comprises of multiple surround-view fisheye cameras and multiple tasks like segmentation and soiling detection. The OmniScape dataset [62] includes semantic segmentation, depth map, intrinsic parameters of the cameras, and the dynamic parameters of the motorcycle. The Waymo Open dataset [63] is a labeled panoramic video dataset for panoptic image segmentation.

Aiming at improving the accuracy of optical flow estimation, OmniFlow [64] is a synthetic omnidirectional human optical flow dataset with images of household activities with a FoV of 180°. OmniFlowNet [22] renders a test set of panoramic optical flow only for validation, using simple geometric models based on Blender. Replica360 [23] implements an ERP camera model for the Replica rendering pipeline [65] and contains ground-truth optical flow in the equirectangular format for validation. SynWoodScape [28] is a synthetic fisheye surround-view dataset with ground truth for pixel-wise optical flow and depth estimation. OmniPhotos [29] is a fast 360° panoramic VR photography method with an released outdoor dataset, but it cannot obtain the ground truth of optical
points. Now we only consider two arcs where there are actually infinite arc trajectories between these two.

A. Definition of 360° optical flow

The spherical image does not contain any boundaries, and the coordinates are continuous in any direction on the image [22]. However, a boundary parallel to the meridian is naturally introduced in the process of unfolding the spherical image into an equirectangular image as shown in Fig. 2. Given any point \( A \) on the sphere, which moves to another point \( B \) after time \( t \). Due to the cyclic nature of the sphere itself, there are actually infinite arc trajectories between these two points. Now we only consider two arcs \( AC_1B \) and \( AC_2B \) whose range are less than the circumference of the great circle, where \( C_1 \) and \( C_2 \) are the vertices of the arcs at both ends, respectively. It is easy to find that these two arcs together form a great circle on the sphere. In the process of spherical unfolding, we can map these two points to \( A' \) and \( B' \) on the equirectangular image plane \( I_x \in \mathbb{R}^W \times H \), respectively, according to the forward ERP:

\[
\begin{align}
\{ x &= L(\phi - \phi_0)\cos\theta_1, \\
y &= L(\theta - \theta_0),
\end{align}
\]

where \( x \) and \( y \) are Cartesian coordinates of the image plane. \( \theta \in (-\frac{1}{2}\pi, \frac{1}{2}\pi), \phi \in (-\pi, \pi) \) are the unit spherical coordinate pitch and yaw, \( \phi_0, \theta_0 \) are central meridian and central parallel, respectively. \( \theta_1 \) are the standard parallels. \( L \) is the scaling factor. Therefore, the cyclicity of a great circle on the sphere, is reflected in the cyclicity of the vertical boundary on the equirectangular image:

\[
\delta x = L\cos\theta_1 \cdot (\delta \phi \bmod 2\pi),
\]

where \( \delta x \) and \( \delta \phi \) denote the variation of Cartesian abscissa and yaw, respectively. \((a \bmod b)\) indicates \( a \) modulo \( b \). Considering a pair of an attended image and a target image, pixels moving out the image boundary on one side will locate to the other side of the image. Thus, there are two 2D motion vectors that connect the source and target points: one is connected along the interior of the equirectangular image, whereas the other points outside the image boundaries. These two flow vectors together form a great circle on the spherical image, one shorter and one longer.

For the classical definition of optical flow, given two frames of sequence equirectangular RGB images \( I_1 \) and \( I_2 \), we estimate the dense motion vector \((u, v)\) from each pixel \((x, y)\) of \( I_1 \) to each pixel \((x', y')\) of \( I_2 \), that is, the optical flow field \( V \), which gives the per-pixel mapping relationship between the source and target. However, classical optical flow cannot track pixels that move outside the image boundaries, and cannot reflect the boundary circulation of panoramic optical flow. Thus, we define 360° optical flow \( V_{360} \) as the shortest path from source to target along the great circle between them, which naturally limits the scalar value of lateral optical flow to \( u \leq 180^\circ \). For ground-truth flow field \( \bar{V}_{GT}(x) = (u, v) \) at pixel index \( x \) of equirectangular images, we can easily convert the optical flow to 360° flow:

\[
V_{360}(x) = \begin{cases} (u - W, v), & \frac{1}{2} W < u \leq W; \\ (u + W, v), & -W \leq u < -\frac{1}{2} W; \\ (u, v), & \text{otherwise.} \end{cases}
\]
Flow distortion to this distortion, we put forward to perform distortion on equirectangular images. To adapt the distortion. The models trained on perspective images suffer of straight lines distorted. Relative to perspective images, the B. Data Augmentation with Flow Distortion

In optics, distortion is a map projection which makes the classical optical flow, which can be used to align temporal coordinate distortion function $F$ inversion function of $F$ in Fig. 4. The comparison between RGB image distortion and optical flow distortion. Since the optical flow of grid points has also been modified during distortion, it should be calibrated before interpolation.

Given a dense cyclic optical flow field $V_{360}$, we can always find the mapping point $(x', y')$ on $I_2$ from every pixel $(x, y)$ on $I_1$, i.e., cyclic optical flow maintains the temporal continuity of classical optical flow, which can be used to align temporal features when considering boundary cyclically.

B. Data Augmentation with Flow Distortion

In optics, distortion is a map projection which makes the straight lines distorted. Relative to perspective images, the equiangular transformation can be regarded as a kind of distortion. The models trained on perspective images suffer from the distortion on equiangular images. To adapt the models to this distortion, we put forward to perform Flow Distortion Augmentation (FDA) on the training samples as a novel data augmentation method.

The distortion of flow is a non-trivial task comparing to general image distortion (Fig. 4). For the properties that adhere to the pixels (e.g., RGB or depth), their values would not be modified during distortion. However, the initial and terminal points of optical flow would both be distorted during distortion. To estimate the exact optical flow of a distorted frame, we should calibrate the optical flow of its grid points before interpolation. Given an undistorted initial point $x_u = (x_u, y_u)$, the flow field $V_u$, and a coordinate distortion function $F$ that maps a distorted coordinate to a calibrated coordinate, the calibrated flow field $V_c$ can be obtained by:

$$\begin{align*}
V_c(x_d) &= F'(x_u + V_u(x_u)) - F'(x_u), \\
x_d &= F'(x_u),
\end{align*}$$

where $x_d = (x_d, y_d)$ is the distorted coordinate and $F'$ is the inversion function of $F$. There are multiple choices for the coordinate distortion function $F$. In this work, we consider the radial distortion and equirectangular distortion, both resulting a remarkable enhancement, which will be discussed in Sec. V-C.

We use the following mapping function $F_r : F(x_u) \rightarrow x_d$ to model the radial distortion:

$$\begin{align*}
x_d &= P(r)(x_c + (x_u - x_c)) , \\
y_d &= P(r)(y_c + (y_u - y_c)),
\end{align*}$$

where $(x_c, y_c)$ is the distortion center (the intermediate point of image by default), $P(x)=x+k_2x^2+k_4x^4$ is a polynomial and $r$ is the Euclidean distance from $(x_u, y_u)$ to $(x_c, y_c)$. In practice, we set $k_2\sim U(-10^{-6}, 10^{-6}), k_4\sim U(-10^{-14}, 10^{-14})$, which are empirically set and achieve reasonable augmentation effects for images of different resolutions.

For equirectangular distortion $F_e : F(x_u) \rightarrow x_d$, we transform the coordinates via spherical coordinate system. We first map $x_u$ on equirectangular image to $x_s = (x_s, y_s, z_s)$ on unit sphere by:

$$\begin{align*}
x_s &= \sin \frac{\pi x_u}{W} \cos \frac{2 \pi y_u}{H}, \\
y_s &= \sin \frac{\pi y_u}{H} \sin \frac{2 \pi x_u}{W}, \\
z_s &= \cos \frac{\pi y_u}{H},
\end{align*}$$

We then apply random 3D rotation to $x_s$ by $x_s^T \leftarrow R_z(\theta_z)R_y(\theta_y)x_s^T$, where $R_y(\theta_y)$ and $R_z(\theta_z)$ are standard 3D rotation matrices about y-axis and z-axis with $\theta_y \sim U(0, \pi)$ and $\theta_z \sim U(0, 2\pi)$:

$$\begin{align*}
R_y(\theta_y) &= \begin{bmatrix}
\cos \theta_y & 0 & \sin \theta_y \\
0 & 1 & 0 \\
-\sin \theta_y & 0 & \cos \theta_y
\end{bmatrix}, \\
R_z(\theta_z) &= \begin{bmatrix}
\cos \theta_z & -\sin \theta_z & 0 \\
\sin \theta_z & \cos \theta_z & 0 \\
0 & 0 & 1
\end{bmatrix}.
\end{align*}$$

Finally, $x_s$ is transformed to the perspective coordinate via:

$$\begin{align*}
x_d &= \frac{W}{2 \tan \frac{\theta_h}{2}} x_s + \frac{W}{2}, \\
y_d &= \frac{H}{2 \tan \frac{\theta_v}{2}} y_s + \frac{H}{2},
\end{align*}$$

where $\theta_h, \theta_v$ are the horizontal and vertical FoV of the perspective image drawn from $U(\frac{\pi}{4}, \frac{3}{4} \pi)$ respectively.

The visualizations of FDA-R and FDA-E are shown in Fig. 5. Notice that the color of the optical flow changes with the distortion, which is due to that the vector distortion affecting the modulo value of the optical flow. The deformation of FDA-E is homogeneous with that introduced by ERP, while the deformation introduced by FDA-R is radially variable. Taking FDA-E as an example, the position of the color image and optical flow on the spherical surface will change randomly in each iteration instead of being fixed, which improves the
robust representation learning ability of the model against distortions. Therefore, the model is able to gradually learn how to handle features with different latitude and longitude on the entire spherical image from the source pinhole data. However, due to the limited FoV of pinhole images, the number of available supervision pixels in FDA-E is actually reduced compared to FDA-R, thus it is necessary to explore the effects of two different optical flow distortion techniques on the distortion robustness of the model. It is verified that FDA improves the adaptation of model by introducing the distorted images to the training data. The ablation experiment of FDA is comprehensively discussed in Sec. V-C.

C. Training with Deformable Receptive Field Encoder

Unlike pinhole images, equirectangular images suffer from severe geometric distortions in panoramic dense prediction [21], [24]. While our flow distortion augmentation helps address the deformations from the perspective of training data, classical CNN-based encoders are still limited by the fixed geometry of the convolution kernels, and has insufficient learning ability for deformable features. Therefore, we propose to replace the first convolutional layer of the encoder with deformable convolution [26] when dealing with 360° contents, endowing the model with a more flexible receptive field. Given a deformable convolution kernel, we extract features at K sampling locations, the weight and grid-specified offset at the k-th location are denoted by \( w_k \) and \( g_k \), respectively. In our practice, we replace the feature encoder and context encoder with two deformable convolution layers with a kernel size of 7×7, thus the kernel is defined with \( K=49 \) and \( g_k \in \{(-3,-3),(-3,-2),\ldots,(0,0),\ldots,(3,2),(3,3)\} \).

The distortion-aware features \( F_d \) at each position \( g_0 \) can be obtained via:

\[
F_d(g_0) = \sum_{k=1}^{K} w_k \cdot I(g_0 + g_k + \Delta g_k) \cdot \Delta o_k, \quad (9)
\]

where \( I \in R^{H \times W} \) is the panorama input, \( \Delta g_k \) and \( \Delta o_k \) are learnable offset and modulation scalar respectively, which are inferred via another convolutional layer:

\[
\{\Delta g_k\}_{k=1}^{K} = \tanh(C_{off}(I)[0:2K]), \quad \{\Delta o_k\}_{k=1}^{K} = \sigma(C_{off}(I)[2K:3K]), \quad (10)
\]

where \( C_{off} \) is a set of convolutional layers, \([a:b]\) denotes the channel slice from index \( a \) to index \( b \), \( \tanh \) and \( \sigma \) represent the Tanh and Sigmoid activation function, respectively. In Sec. V-C, we will show that the use of deformable receptive field encoder further enhances the robustness of the model to distorted images.

D. Inference with Cyclic Flow Estimation

In order to directly infer 360° cyclic flow from equirectangular contents, and relieve the stress of the model in long-distance displacement estimation, we introduce a Cyclic Flow Estimation (CFE) method based on the geometric nature of panoramas. The structure of CFE is shown in Fig. 5. CFE exploits the cyclicity of the left and right boundaries of equirectangular images, and it is compatible with any optical flow network based on an encoder-decoder structure, e.g., RAFT [19] or CSFlow [20].

Specifically, we first use a convolutional network as the encoder \( e(\cdot) \) to extract features \( F_1, F_2 \in R^{C \times H \times W} \) from the input two frames of equirectangular images \( I_1, I_2 \in R^{h \times w} \). Then, the features are split along the horizontal centerline into \( F_{a1}, F_{a2} \in R^{C \times \frac{H}{2}} \) and \( F_{b1}, F_{b2} \in R^{C \times \frac{H}{2}} \), respectively. We regard the process of feature encoding as rigid, that means, we should obtain exactly the same features for the same image input. Therefore, when swapping the left and right regions of the input image, the resulting feature maps should also be approximately left-right swapped. Based on the above observations, we can regroup the feature maps as two feature pairs \( P_1, P_2 \in R^{2 \times C \times H \times W} \):

\[
P_1 = \{F_{a1} \oplus F_{b1}, F_{a2} \oplus F_{b2}\}, \quad P_2 = \{F_{b1} \oplus F_{a1}, F_{b2} \oplus F_{a2}\}. \quad (11)
\]

where \( \oplus \) means a concatenate operation. Since the RAFT structure [19] contains an additional context encoder \( e(\cdot) \), the context feature maps \( C_{a1}, C_{b1} \in R^{C \times \frac{H}{2}} \) extracted from \( I_1 \) should also be regrouped into \( P_{c1}, P_{c2} \in R^{C \times H \times W} \):

\[
P_{c1} = \{C_{a1} \oplus C_{b1}\}, \quad P_{c2} = \{C_{b1} \oplus C_{a1}\}. \quad (12)
\]

We then stack the feature pairs with context respectively, which will be further sent to the decoder \( d(\cdot) \). Subsequently, the decoder will estimate two flow fields \( \mathbf{V}, \mathbf{V}' \in R^{2 \times h \times w} \).
The flow estimations are split along the horizontal centerline into $V_{a_1}, V_{b_1} \in \mathbb{R}^{2 \times h \times \frac{w}{2}}$ and $V'_{a_1}, V'_{b_1} \in \mathbb{R}^{2 \times h \times \frac{w}{2}}$. Assuming that the estimation is unbiased, for any pixel $(x, y)$ in area $a$, we consider that $V_{a_1}(x, y)$ and $V'_{a_1}(x, y)$ form a pair of complementary optical flows end to end, and these two 2D motion vectors together form a great circle on the sphere. The same is true for area $b$. According to our definition of 360° optical flow, the final 360° flow field $\hat{V}$ is obtained:

$$\hat{V} = \min(V_{a_1}, V'_{a_1}) \oplus \min(V_{b_1}, V'_{b_1}).$$

We emphasize again that CFE is a generic flow estimation method based on the assumption that the encoding process should be rigid, which can replace the large displacement estimation with the small displacement estimation when dealing with panoramic contents. According to our analysis of the geometric nature of consecutive panoramic frames in Sec. III-A, CFE is able to cope with the intrinsically most difficult part of long-range cyclic estimation in panoramic optical flow, without having to estimate dozens of times on the tangent plane of the regular polyhedron like the previous method [23]. Considering that large displacement estimation is much more challenging for the model, CFE can significantly enhance the prediction reliability. With the proposed CFE method, we eliminate redundant encoding calculations, and ensure computational efficiency while accurately estimating 360° optical flow. Another naive idea is to use circular convolutions to replace classical convolutional layers. However, we will show in ablation studies (Sec. V-C) that this method only has a limited circularity for cyclic flow, and thus it is not suitable for panoramic flow estimation.

IV. Flowscape: Established Synthetic Dataset

End-to-end learning of deep neural networks requires a large amount of annotated ground truth data. Although for pinhole cameras this can be partly resolved by using scanning LiDARS and multiple sensors [68], [69], such an approach is impractical for 360° images, considering that panoramic camera and LiDAR will block each other and have a large divergence in their resolutions. In addition, the point cloud data given by LiDARS is sparse, thus it is difficult to obtain dense ground-truth values of optical flow in the real world. Even when these flaws are patched using algorithms during acquisition, additional errors are still introduced. On the other hand, synthetic datasets are popular for learning flow estimation due to the lack of real-world training data [32], [66], [70]. Extensive investigations have demonstrated that generalization from synthetic- to real scenes is feasible for optical flow tasks [19], [20], [71].

Flowscape dataset: We notice that there is a lack of an open panoramic optical flow dataset that can be used for training and credible numerical evaluation. Therefore, we advocate to generate a dataset with ground-truth flow by synthesizing both the color image and flow via the CARLA simulator [27]. Specifically, we use eight open-source maps given by CARLA. Our virtual collection vehicle contains 6 pinhole color cameras, 6 pinhole optical flow cameras, and 6 pinhole semantic cameras, all of which have a FoV of 90°×90°, are in the same spatial viewpoint and keep synchronized timestamps. Taking color images as an example, six orthogonal viewing angles are obtained to form a cubemap panorama $\{I_f, I_r, I_b, I_l, I_u, I_d\} \in \mathbb{R}^{h \times w}$, including front, right, back, left, top, and bottom view. We can then acquire the equirectangular image $I_r \in \mathbb{R}^{H \times W}$ with a FoV of 180°×360° by using a cubemap-to-equirectangular algorithm as a post-processing. Given four horizontally views $\{I_f, I_r, I_b, I_l\}$ of the cubemap format, we can calculate their corresponding coordinates $(x, y)$ on the equirectangular image plane:

$$\begin{align*}
  x &= \frac{W}{2} \cdot \tan\left(\frac{\phi - m \frac{\pi}{2}}{H}\right), \\
  y &= \frac{H}{2} \cdot \cos\left(\theta - m \frac{\pi}{2}\right),
\end{align*}$$

(14)

where the view index $m=\{1, 2, 3, 4\}$, $\theta \in (-\frac{\pi}{2}, \frac{\pi}{2})$, $\phi \in (-\pi, \pi)$ are the angular coordinates. For the upper and lower views $\{I_u, I_d\}$:

$$\begin{align*}
  x &= \frac{W}{2} \cdot \tan\left(\frac{\pi}{2} - \theta\right) \sin(\phi), \\
  y &= \frac{H}{2} \cdot \tan\left(\frac{\pi}{2} - \theta\right) \cos(\phi + n\pi),
\end{align*}$$

(15)
where the view index \( n=\{0,1\} \). Given 6 views in the cubemap format panorama with a resolution of 1024×1024, the reprojection latency of the panoramic image is 0.37 s, and the panoramic optical flow takes 1.29 s, both test on the Intel i5-12600K CPU with Python 3.9 implementation.

We set 100~120 initial collection points on each of the 8 open source maps, and all of them are on the road. During collection, a tracing renderer is used to render our dataset by placing these pinhole cameras at a starting position \( P \in \mathbb{R}^3 \) in the scene, which is randomly sampled from the initial collection points of the map. For each map, we augment the dataset by changing weather, including sunny (62.5%), cloud (12.5%), fog (12.5%), and rain (12.5%) to form FlowScape and assess the robustness of optical flow estimation in various conditions. During the collection process, as the number of vehicles and pedestrians increases, the rendering overhead will increase slightly. For purpose of controlling the stability of the data collection while maintaining the richness of the foreground, we set the generation upper limit of vehicles and pedestrians to 200 for all the maps. In order to ensure a good diversity of the synthetic data, we only gather 100 frames with a frame rate of 30 Hz for each position. Considering the unreliable optical flow at infinity such as that on points in the sky, we additionally provide ground-truth values of pixel-wise semantic segmentation for selection, which could also be beneficial for panoramic semantic understanding tasks [24], [25]. The semantic labels follow CARLA’s setting (Fig. 6). Overall, FlowScape provides 6,400 panoramic images of diverse street scenes, each with ground truth of both optical flow and semantic labels.

**Photoconsistency analysis:** As shown in Tab. I, we compare the existing panoramic optical flow datasets. SynWoodScape [28], OmniFlowNet [22], and Replica360 [23] are three small datasets for evaluating panoramic optical flow. Due to their small size, they are not suitable for the training of neural network based methods. We further explore the photoconsistency [67] by introducing photometric error (PE) and warped photometric error (WPE) to evaluate the ground-truth optical flow quality of the dataset when only forward flow is given:

\[
PE = \frac{1}{HW} \sum_x |I_1(x) - I_2(x)|, \tag{16}
\]

\[
WPE = \frac{1}{HW} \sum_x |I_1(x + V_{GT}(x)) - I_2(x)|, \tag{17}
\]

where \( x \) is the pixel index and \( V_{GT} \) is the ground-truth optical flow field. Obviously, the quality of the ground-truth flow is high when WPE is significantly lower than PE, i.e., a high-quality optical flow field can convert one image to the next as much as possible [72]. We consider forward optical flow that results in a reduction in interpolation error of less than 10% to be medium/low-quality ground truth. We perform ground-truth quality analysis on the popular perspective optical flow dataset [32], [66], [70] and these three panorama datasets separately, and the results are shown in Tab. II. Compared to the public OmniFlowNet and our FlowScape datasets, the ground-truth flow of Replica360 dataset seems to be unreliable. Consequently, our quantitative evaluations are performed on the first two datasets.

**V. Experiments**

We conduct experiments using two typical learning-based flow method [19], [20] to verify the proposed PanoFlow framework. We confirm the role of the key components in PanoFlow through ablation experiments. For OmniFlowNet [22] and Yuan et al. [23], we use their official released codes for testing. Unfortunately, neither the code nor the dataset of LiteFlowNet360 [50] is publicly available, therefore we cannot make a fair comparison with it. Since OmniFlowNet is an adaptive method designed for learning-based optical flow networks, we additionally upgrade its backbone from LiteFlowNet2 [48] to RAFT [19] and CSFlow [20] for quantitative experiments to demonstrate that our PanoFlow framework is more generic and effective. We further conduct qualitative comparisons on the public outdoor panoramic dataset OmniPhotos [29] and our PAL-collected panoramic videos.
A. Training Details

Following previous works, we pretrain our model using the FlyingChairs [32]→FlyThings [70] schedule, followed by finetuning on our FlowScape dataset. We divide FlowScape into 5,000/1,400 image pairs for train/test subsets. Considering that the sunny days are the most common weather conditions, the test set of FlowScape covers sunny (57.1%), cloud (14.3%), fog (14.3%), and rain (14.3%). We train our model on an RTX 3090 GPU, implemented in PyTorch. We pretrain on FlyingChairs for 100k iterations with a batch size of 10, then train for 100k iterations on FlyingThings3D with a batch size of 6. Finally, we finetune on FlowScape with a batch size of 6 for another 100k iterations using the weights from the pretrained model. The ablation experiment is performed with 100k training iterations on Chairs, and the batch size is also 10. We time our method using an RTX 3090 GPU. The GRU iteration number is set to 12 during training and inference. We follow RAFT [19] for data augmentation. All experiments are with the same augmentations including occlusion augmentation [73], random rescale, perturbing brightness, as well as contrast augmentation, saturation augmentation, and hue augmentation.

B. PanoFlow on FlowScape

We evaluate PanoFlow on the FlowScape dataset using the test split. Results are shown in Tab. III, where we split the results based on the weather conditions. The best results are bolded, the second best are underlined. We term the method using the PanoFlow framework as PanoFlow (·). We denote * and ** to distinguish models using FDA-R and FDA-E methods. C+T means that the models are trained on FlyingChairs (C) and FlyingThings (T). F indicates methods using only FlowScape (F) train split for finetuning. When using C+T for training, our method achieves an 11.7% error reduction for RAFT, and a 12.4% error reduction for CSFlow. The results of CSFlow are slightly better than RAFT, which demonstrates its better cross-dataset generalizability. After finetuning on FlowScape, estimating flow under PanoFlow framework can further improve the accuracy. Our PanoFlow (CSFlow) improves EPE from 4.47 to 3.25 (↑27.3%). Interestingly, FDA-R also makes it easier for the model to cope with ERP deformations when trained on the perspective dataset. When we turn off FDA and train on FlowScape, the FDA-E models have a slightly better overall accuracy than FDA-R, but this advantage does not hold in all weather conditions. We believe this is due to the fact that, by introducing deformed optical flow field for training process which is changed randomly in each iteration instead of being fixed, our model is able to extract robust features for computing visual similarity across different distortion modalities.

C. Ablation Studies

To demonstrate the role of each core module in the proposed PanoFlow framework, we perform the ablation studies on FlowScape using the well-known RAFT structure [19]. End-Point-Error (EPE) is used as the evaluation metric. We now describe the findings of each study.

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### TABLE III

**Quantitative results on FlowScape dataset.**

| Training Data Method | Sunny | Cloud | Fog | Rain | All (test) | Diff. |
|----------------------|-------|-------|-----|------|-----------|-------|
|                       | EPE   | EPE   | EPE | EPE  | EPE       |       |
| RAFT [19]            | 16.57 | 11.16 | 15.04 | 17.00 | 15.64 | - |
| PanoFlow (RAFT)      | 14.93 | 11.25 | 13.88 | 13.36 | 14.03 | ↑10.3% |
| PanoFlow (RAFT)***   | 14.66 | 11.10 | 13.57 | 13.38 | 13.81 | ↑11.7% |
| CSFlow [20]          | 16.32 | 11.16 | 14.99 | 16.04 | 15.35 | - |
| PanoFlow (CSFlow)*   | 14.74 | 11.18 | 13.64 | 13.42 | 13.89 | ↑9.5%  |
| PanoFlow (CSFlow)**  | 14.27 | 10.74 | 13.03 | 13.34 | 13.45 | ↑12.4% |
| RAFT [19]            | 4.77  | 1.52  | 4.84  | 6.07  | 4.50   | - |
| PanoFlow (RAFT)*     | 3.62  | 1.38  | 3.60  | 4.25  | 3.39   | ↑24.7% |
| PanoFlow (RAFT)**    | 3.58  | 1.41  | 3.63  | 4.17  | 3.36   | ↑25.3% |
| CSFlow [20]          | 4.70  | 1.46  | 4.79  | 6.24  | 4.47   | - |
| PanoFlow (CSFlow)*   | 3.56  | 1.47  | 3.56  | 3.94  | 3.31   | ↑26.0% |
| PanoFlow (CSFlow)**  | 3.46  | 1.35  | 3.59  | 3.98  | 3.25   | ↑27.3% |

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### TABLE IV

**Ablations on Flow distortion augmentation.**

| Augmentation | FDA-R | FDA-E | Sunny | Cloud | Fog | Rain | All (test) |
|--------------|-------|-------|-------|-------|-----|------|-----------|
|              | EPE   | EPE   | EPE   | EPE   | EPE | EPE  | EPE       |
|              |       |       |       |       |     |      |           |
| -            | -     | 18.53 | 12.88 | 17.00 | 18.02 | 17.43 |
| ✓            | -     | 17.86 | 12.63 | 16.60 | 17.59 | 16.89 |
| ✓            | ✓     | 16.65 | 11.67 | 15.48 | 16.50 | 15.75 |

---

**Flow Distortion Augmentation:** We explore the role of two different flow distortion variants on the model’s ability to adapt from pinhole to panoramic domains. The results are shown in Tab. IV. Both FDA-R and FDA-E can help models to overcome ERP deformation, which indicate that distorted optical flow is beneficial for the model to learn robust features. Although the total number of effectively supervised pixels is reduced in FDA-E, its modality is closer to ERP, thus the model using FDA-E gains an advantage. In the following ablation experiments, we use the FDA-E model by default.

**Core Components:** Tab. V shows how performance varies as each core component (FDA-E: flow distortion augmentation in ERP format; CFE: cyclic flow estimation; DCN: deformable receptive field encoder) of our model is removed. We can see that every component contributes to the overall performance. We find that CFE has the greatest impact on accuracy. The result is surprising, considering that this method that can be used without any retraining. This also reveals that the PanoFlow framework can easily benefit from advances in general optical flow networks. When all the key components are in place, the model performs optimally in all weathers. In the following experiments, we use the “full” version of our method (last row of Tab. V).

**Cyclic Flow Estimation:** We additionally conduct an ablation study based on PanoFlow (RAFT) that has been finetuned on FlowScape to further investigate how the setting of the CFE affects the accuracy and efficiency. Tab. VI shows that CFE improves the performance the most in the default setting.
TABLE V
ABLATIONS ON CORE COMPONENTS OF PANOFLOW.

| Core Components | Sunny | Cloud | Fog | Rain | All (Test) |
|-----------------|-------|-------|-----|------|------------|
| FDA-E CFE DCN   |       |       |     |      |            |
| - - -            | 18.53 | 12.88 | 17.00 | 18.02 | 17.43      |
| ✓ - -            | 16.65 | 11.67 | 15.48 | 16.50 | 15.75      |
| - ✓ -            | 16.56 | 12.46 | 15.25 | 15.35 | 15.62      |
| - - ✓            | 18.11 | 12.69 | 16.66 | 17.78 | 17.08      |
| - ✓ ✓            | 15.93 | 12.13 | 14.69 | 15.03 | 15.08      |
| ✓ - ✓            | 16.44 | 11.41 | 15.25 | 16.07 | 15.50      |
| ✓ ✓ ✓            | 14.72 | 11.28 | 13.69 | 13.84 | 13.96      |
| ✓ ✓ ✓ ✓          | 14.55 | 11.09 | 13.57 | 13.42 | 13.75      |

TABLE VI
CYCLIC FLOW ESTIMATION ABLATION.

| CFE Settings            | FlowScape (test) | Avg. Diff. | Latency |
|-------------------------|------------------|------------|---------|
|                         | sunny | cloud | fog | rain |            |
| Baseline                | 4.77  | 1.52  | 4.84 | 6.07 | 4.50       | 0.10s     |
| Circular Convolution    | 5.72  | 2.73  | 6.02 | 7.50 | 5.59       | 0.11s     |
| Double Estimation       | 3.81  | 1.68  | 3.86 | 4.29 | 3.58       | 0.18s     |
| Half Zero Padding       | 3.82  | 1.54  | 3.74 | 4.57 | 3.59       | 0.24s     |
| Half Same Padding       | 31.5  | 23.5  | 22.1 | 35.8 | 29.6       | 0.13s     |
| Default                 | 3.58  | 1.41  | 3.63 | 4.17 | 3.36       | 0.13s     |

Circular Convolution: In order to explore the ability of circular convolution to capture large-displacement cyclic visual similarity, we replace the convolutional layers in the model with circular convolutions, where experimental results show they do not help performance. We believe that this is because the circular convolution uses a simple padding operation to warp the image, and the introduced cyclicity is insufficient, considering that the end point of the $360^\circ$ optical flow may fall within the area $[0, \frac{W}{2}]$ outside the left and right boundaries of the panoramic image. However, most of the flow vectors are still given in the direction of the traditional optical flow, which makes it a disadvantage in $360^\circ$ flow estimation ($\downarrow 19.5\%$). Double Estimation: A naive idea is to swap the left and right regions directly, estimate twice and take the respective minimum values. This does improve the accuracy, but the time complexity is also doubled. It also confuses the model during encoding the false image boundary introduced by the swap operation. Half Zero Padding: Based on the above observations, we naturally associate whether the another region’s feature will interfere with the results of the region of interest when decoding. Thus, we try replacing half of the feature maps with empty tensors, resulting in one encoding and four decodings. We find that it has no advantages over the default setting. Half Same Padding: We further replace the zero feature with same feature of the region of interest. The same features make the model face two confusing scene cues at the same time when calculating the visual similarity, which leads to terrible performance regression. Default: The performance improvement brought by CFE is the most significant in the default setting, and its time complexity is only modest.

![Fig. 8.](image)

We further explore the horizontal distribution of the gain introduced by CFE. As shown in Fig. 8, CFE improves the model’s ability to cope with cross-boundary optical flow, which is an essential difficult part of panoramic flow estimation. On FlowScape, CFE seems to cause a slight degradation near the right boundary, which we believe is due to the fact that the road features of FlowScape are highly similar, causing the model to confuse the road on both sides of the boundary during cyclic inference. And our virtual collection vehicle goes straight ahead, resulting in less cross-boundary optical flow. On the OmniFlowNet dataset, it can be observed that the accuracy is significantly improved in the range of $270^\circ \sim 360^\circ$ in FoV. This is reasonable because the dataset only contains forward- and rightward movements, and the crossing of boundaries generally occurs on the right side of the image. Considering real-world cases, the vehicle cannot move completely straight ahead along the lane line, and traffic accidents might occur when the vehicle turns, thus, CFE is ideally suitable for real driving scenarios.

d. Comparison with the State-of-the-Art

Quantitative Comparison on Synthetic Data: OmniFlowNet [22] is a state-of-the-art CNN adaption model for optical flow estimation in omnidirectional images which can be built on general CNN architectures for perspective images.
We reproduce the OmniFlowNet using MMFlow [74] and compare it with our model. Since OmniFlowNet is built on LiteFlowNet2 [48], which is inconsistent to our baseline, we also apply the architecture of OmniFlowNet to RAFT and CSFlow. As shown in Tab. VII, we evaluate the models on the OmniFlowNet dataset [22] with all three scenarios (i.e., CartoonTree (Cart.), Forest (Forest), LowPolyModels (Poly.)), and our FlowScape dataset. All models are trained on FlyingChairs (C) + FlyThings (T), with “-ft” indicating that the model was additionally fine-tuned on the FlowScape data. We also report the accuracy of the icosahedron tangent-plane panoramic flow estimation method [23] on both datasets.

| Method                        | OmniFlowNet Dataset | FlowScape (test) | Latency |
|-------------------------------|---------------------|------------------|---------|
|                               | Cart. Forest Poly. Avg. Diff. | Avg. Diff. |         |
| OmniFlowNet [22]              | 3.37 4.78 6.73 12 7 22.16 | - 0.02s |
| Yuan et al. [23]              | 9.13 14.27 10.22 11.21 | 5.7 20.35 | 10.48s |
| OmniFlowNet (RAFT)            | 4.84 8.70 6.74 6.76 | 5.06% 19.61 | 11.5% 0.43s |
| OmniFlowNet (CSFlow)          | 4.74 6.86 6.52 6.64 | 6.74% 19.47 | 12.1% 0.44s |
| OmniFlowNet (RAFT)-ft         | 3.55 7.28 5.28 3.57 | 24.6% 14.33 | 35.3% 0.43s |
| OmniFlowNet (CSFlow)-ft       | 3.57 7.21 5.50 5.43 | 23.7% 15.33 | 30.8% 0.44s |
| PanoFlow (RAFT)**             | 3.37 4.78 6.73 12 7 22.16 | - 0.02s |
| PanoFlow (RAFT)**-ft           | 2.71 4.14 5.29 4.05 | 43.1% 13.81 | 37.7% 0.13s |
| PanoFlow (RAFT)**-ft           | 2.31 3.53 4.91 3.58 | 49.8% 3.39 | 84.7% 0.13s |
| PanoFlow (RAFT)**-ft           | 1.97 3.29 4.24 3.17 | 55.5% 3.36 | 84.8% 0.13s |
| PanoFlow (CSFlow)**           | 3.81 4.76 6.92 5.16 | 27.4% 13.89 | 37.3% 0.14s |
| PanoFlow (CSFlow)**-ft         | 2.83 4.58 5.57 4.33 | 59.2% 13.45 | 39.3% 0.14s |
| PanoFlow (CSFlow)**-ft         | 2.02 3.51 4.48 3.34 | 53.1% 3.31 | 85.1% 0.14s |
| PanoFlow (CSFlow)**-ft         | 1.92 3.53 4.37 3.27 | 54.1% 3.25 | 85.3% 0.14s |

We further investigate the practical performance of the proposed PanoFlow solution on real data, we install a panoramic anular lens (PAL) system with an FoV of $60^\circ \times 360^\circ$ on top of a mobile robot (see Fig. 12), which navigates around the campus according to the remote control. As shown in Fig. 11, we collect panoramic videos of campus street scenes and compare our approach with the results given by OmniFlowNet [22] and the method from Yuan et al. [23]. Although the robot’s perspective and FoV are significantly different to that of the virtual camera used in the FlowScape for training, PanoFlow still gives clear and sharp optical flow estimation. For other methods, estimating directly on PAL images will lead to epic failures. Therefore, we convert the PAL video stream to the standard ERP format with an aspect ratio of 2:1 before estimation for each method except PanoFlow. This also reveals that these methods will face additional computational overhead when used on real panoramic shots, as their methods are only designed for complete ERP data.
### Fig. 9. Error heatmap visualizations on FlowScape test split and OmniFlowNet datasets [22]. PanoFlow can easily cope with the challenges introduced by image distortion in high-latitude regions and provide a clear and smooth panoramic flow field in one shot.

| Reference Frame | OmniFlowNet | Yuan et al. | OmniFlowNet (RAFT) | Ours |
|-----------------|-------------|-------------|--------------------|------|
| ![Image](image1) | ![Image](image2) | ![Image](image3) | ![Image](image4) | ![Image](image5) |
| ![Image](image6) | ![Image](image7) | ![Image](image8) | ![Image](image9) | ![Image](image10) |
| ![Image](image11) | ![Image](image12) | ![Image](image13) | ![Image](image14) | ![Image](image15) |

### Fig. 10. Qualitative results on the OmniPhotos [29] dataset. PanoFlow successfully generalizes from synthetic dataset to real scenes, and the panoramic flow field visualizations are clean and discriminative while well preserving the details of the image.

| Reference Frame | OmniFlowNet | Yuan et al. | OmniFlowNet (RAFT) | Ours |
|-----------------|-------------|-------------|--------------------|------|
| ![Image](image16) | ![Image](image17) | ![Image](image18) | ![Image](image19) | ![Image](image20) |
| ![Image](image21) | ![Image](image22) | ![Image](image23) | ![Image](image24) | ![Image](image25) |
| ![Image](image26) | ![Image](image27) | ![Image](image28) | ![Image](image29) | ![Image](image30) |

Specifically, for pedestrian and fast-moving vehicles in the foreground of the panoramic images, PanoFlow does not confuse them with the motion of the background, even if they are deformed to varying degrees. Edges are blurred and indistinguishable in OmniFlowNet’s background flow estimation, whereas the outlines of street scenes are still sharp and recognizable in PanoFlow’s output results. Compared with the method proposed by Yuan et al., PanoFlow gives optical flow with better continuity, and the detailed features are also well preserved. We conclude that our method outperforms the previous state-of-the-art work for both foreground- and background motion estimations, showing excellent synthetic-to-real generalizability.

### E. Efficiency Analysis

We report the parameter counts, memory requirements during inference, inference time, and the accuracy performance as shown in Tab. VIII. Accuracy is determined by the performance on the FlowScape (test) after training on C+T+F. The image size is 512x1024. RAFT takes 2.67GB memory while our approach takes 2.78GB memory. Due to the additional global context introduced by the decoder in CSFlow, the memory consumption of PanoFlow (CSFlow) is larger than the former. Overall, the results demonstrate that the computational overhead of PanoFlow is low, in contrast to the significant performance improvement, and is therefore suitable for intelligent vehicles to perceive surrounding temporal cues.
Fig. 11. Qualitative comparison of existing methods in outdoor-campus 360° image sequences that captured by our PAL camera. PanoFlow gives optical flow with clear and sharp boundaries for both foreground and background, which means stronger generalization ability for the real-world.

(a) Mobile Robot  (b) PAL Camera

Fig. 12. (a) Our outdoor mobile robot is equipped with a Panoramic Annular Lens (PAL) camera and a laptop. (b) PAL for capturing outdoor panoramic video streams.

| Method       | Parameters | GPU Memory | Time   | △Accuracy |
|--------------|------------|------------|--------|-----------|
| RAFT [19]    | 5.3M       | 2.67GB     | 0.10s  | -         |
| PanoFlow (RAFT)* | 5.3M       | 2.78GB     | 0.13s  | +24.7%    |
| PanoFlow (RAFT)** | 5.3M       | 2.78GB     | 0.13s  | +25.3%    |
| CSFlow [20]  | 5.6M       | 3.42GB     | 0.10s  | -         |
| PanoFlow (CSFlow)* | 5.6M       | 4.04GB     | 0.14s  | +20.0%    |
| PanoFlow (CSFlow)** | 5.6M       | 4.04GB     | 0.14s  | +27.3%    |

TABLE VIII
RUNNING TIME, PARAMETERS, AND MEMORY REQUIREMENT.

F. Failure Case Analysis

As shown in Fig. 13, when there is overexposure in the middle area of the image, the optical flow continuity on both sides will be reduced during cyclic estimation, which is reasonable because the features on both sides become difficult to distinguish and confuse the decoder of the optical flow network. Overcoming this limitation requires some form of supervision or better backbones, e.g., reasoning about panoramic semantics, reasoning about spatio-temporal features in video, or reasoning about fusion with high dynamic range sensors, such as event cameras. Future work can be dedicated to transferring our method to these approaches.

VI. CONCLUSION

In this paper, we proposed PanoFlow, a flexible framework for estimating 360° optical flow using flow distortion augmentation, cyclic flow estimation, and deformable receptive filed encoder. We also proposed FlowScape, a publicly available synthetic panoramic optical flow dataset, which can be used for training and evaluation. We have proved through a large number of quantitative experiments that our PanoFlow is compatible with any optical flow methods of an encoder-decoder structure, which significantly improves the accuracy of panoramic flow estimation while ensuring computational efficiency. PanoFlow achieves state-of-the-art performance on both public OmniFlowNet dataset and our FlowScape. PanoFlow also demonstrates strong synthetic-to-real generalizability in the real world, giving high-quality panoramic flow fields for both foreground and background. We look forward to further exploring the adaptability of the PanoFlow framework for other downstream panoramic tasks.
In the future, we aim to explore other panoramic scene understanding tasks, such as the fusion of panoramic camera and LiDAR sensor for an entire and complete semantic and temporal surrounding perception. Furthermore, we plan to exploit synthetic data to study robust scene perception under corner cases such as risky driving and sensor failures to alleviate the long-tail problem in autonomous driving. We also have the intention to look into 3D scene flow estimation based on panoramic cameras. In addition to panoramic cameras with ultra-wide FoV, we are also interested in exploring optical flow estimation for event cameras with ultra-high dynamic range.

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