Unsupervised Learning of Optical Flow With Non-Occlusion From Geometry

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Abstract—Optical flow estimation is a fundamental problem of computer vision and has many applications in the fields of robot learning and autonomous driving. This paper reveals novel geometric principles of optical flow based on the insights and detailed definition of non-occlusion. Then, two novel loss functions are proposed for the unsupervised learning of optical flow based on the geometric principles of non-occlusion. Specifically, after the occlusion part of the images are masked, the flow process of pixel coordinate points is carefully considered and geometric constraints are conducted based on the geometric principles of optical flow. First, the optical flow vectors of neighboring pixel coordinate points in the first frame will not intersect during the pixel displacement to the second frame. Secondly, when the cluster containing adjacent four pixel coordinate points in the first frame moves to the second frame, no other pixel coordinate points will flow into the quadrilateral formed by them. According to the two geometrical constraints, the optical flow non-intersection loss and the optical flow non-blocking loss in the non-occlusion regions are proposed. Two loss functions punish the irregular and inexact optical flows in the non-occlusion regions. The experiments on datasets demonstrated that the proposed unsupervised losses of optical flow based on the geometric principles in non-occlusion regions make the estimated optical flow more refined in detail, and improve the performance of unsupervised learning of optical flow. In addition, the experiments training on synthetic data and evaluating on real data show that the generalization ability of optical flow network is improved by our proposed unsupervised approach. Our codes are opensourced at: https://github.com/IRMVLab/NeFlow.

Index Terms—Computer vision, deep learning, optical flow estimation, unsupervised learning, occlusion.

I. INTRODUCTION

Optical flow represents the 2D motion and correspondence relationship between two images at the pixel level, which is a fundamental problem in the field of computer vision. Optical flow has many applications in autonomous driving [1], such as visual odometry [2], target tracking [3], moving object detection, and mapping [4], [5]. In addition, the optical flow can be used to analyze the motion attributes of pedestrians and vehicles, so as to realize the dynamic understanding of scenes and decision-making [6]–[8]. With the development of deep learning, good performance of optical flow estimation has been achieved by training on synthetic data [9], [10]. However, the gap between real data and synthetic data makes the supervised models on synthetic data have limited performance in real data. This spawned a large number of unsupervised studies of optical flow to make the trained optical flow network without the gap when applied in real applications [11]–[22]. Besides, the unsupervised method can utilize a large number of videos on the internet. The common basic idea behind the unsupervised learning of optical flow lies in the consistency of RGB channel features between the target image and the reconstructed image. The reconstructed image is obtained by warping the source image utilizing the estimated optical flow field by the neural network model. Then, the neural network model is trained and updated to minimize the difference between the target image and the reconstructed image. This consistency assumption is not satisfied in the occlusion regions of images, so many previous works exploit a lot of methods to mask the occlusion regions [13], [16], [19]–[22]. However, there are seldom studies on the constraints of optical flow on non-occlusion regions. The smoothness loss is for all optical flow in an image. The reconstruction loss utilizes the luminosity constraint, not considering the geometry of the optical flow. In this paper, it is found that there are some geometric principles for optical flow when the occlusion occurs. These principles can enable the network to better estimate optical flow in non-occlusion regions. To our best knowledge, this paper is the first to study the non-occlusion constraints of unsupervised optical flow learning. In this work, we reveal new geometric principles of the optical flow in non-occlusion regions and design two new unsupervised losses for the unsupervised learning of optical flow. Our contributions are as follows:

- By carefully analyzing the motion of each pixel in real 3D space and 2D projected image, non-occlusion is defined in the 2D image in detail. New geometric principles of optical flow in the non-occlusion regions are revealed.
- Based on the insights into the geometric principles of optical flow in the non-occlusion regions, two novel loss functions, the non-intersection loss and the non-blocking loss, are proposed for the unsupervised learning of optical flow. The non-intersection loss defines that optical flows should not cross each other in non-occlusion regions. The
non-blocking loss defines that a pixel coordinate point should not be surrounded by other nearby pixel coordinate points during the pixel motion in non-occlusion regions.

- We integrate our proposed unsupervised losses into a unified framework of unsupervised optical flow and the experiments demonstrated the effectiveness of our proposed losses. The experiments on real dataset, KITTI 2015 dataset [4], [23], show the good generalization ability of our model.

II. RELATED WORK

A. Optical Flow Estimation

Optical flow describes the pixel displacement on a 2D projected image because of the relative 3D motion between objects and the camera for observing [24]. Traditional methods define optical flow estimation as an energy minimization problem based on brightness consistency and spatial smoothness [25]–[27]. With the rapid development of deep learning, optical flow neural network can predict optical flow directly from a pair of images in an end-to-end manner [9], [10]. Ranjan et al. [28] propose the coarse-to-fine pyramid structure to make the network model size much smaller and improve the accuracy. Sun et al. [29] propose the PWC-Net, which performs warp operations and cost volume calculations for each level of the pyramid, showing the strong performance. Yang et al. [30] improve the volumetric layer by using the encoder-decoder architectures, to reduce parameters and achieve better performance. These supervised approaches need numerous data with optical flow labels to achieve better performance. However these data are expensive to obtain [23], [31], and sometimes special methods are even needed to get them [32], which limits the application of these supervised methods.

B. Unsupervised Learning of Optical Flow

The unsupervised approach avoids the need for labels through some regularization and has been the focus of recent research [11]–[22]. The unsupervised method generates the optical flow by learning a function from the unlabeled dataset. As research goes on, the constraints of unsupervised training continue to increase, which allows neural networks to make more full use of unlabeled data, such as edge-aware smoothness [13], photometric consistency loss [14], [17], [19], [20], [27], [33], [34], occlusion estimation [13], [16], [19]–[21], distillation learning based on teacher and student models [17], [18] and so on. UFlow [22] systematically compares those key components in an unsupervised optical flow model to identify which is most effective and chooses the best combination of those components, achieving the better performance in all benchmarks.

Besides those key components of unsupervised optical flow estimation, there are many other improvements. Wang et al. [13] explicitly model occlusion and propose a new warping approach to solve the problem of large estimation errors caused by large motions. Alletto et al. [15] divide the optical flow estimation into two steps: global transformation with homography and refinement by a deeper network, which can make the optical flow estimation more accurate. Janai et al. [16] firstly use multi-frame information for occlusion processing in the unsupervised learning of optical flow. SelFlow [18] utilizes temporal information from multiple frames for better flow estimation. Zhong et al. [35] propose Deep Epipolar Flow which incorporates global geometric constraints into network learning. Flow2Stereo [36] trains a network to estimate both flow and stereo, using triangle constraint loss and quadrilateral constraint loss. DF-Net [19] proposes the cross consistency loss of the depth and pose based rigid flow and optical flow in rigid regions. Ranjan et al. [20] bring forward the idea of competitive collaboration to achieve unsupervised coordinated training of four tasks: depth, camera motion, optical flow, and motion segmentation. Wang et al. [21] jointly estimate pose, depth, and optical flow in an unsupervised method by dividing an image into three parts: the occluded region, the non-rigid region, and the rigid region. Liu et al. [37] propose a new approach that leverages data augmentation to assist self-supervision. Chi et al. [38] propose a single network to combine and improve the three tasks, optical flow, stereo depth, camera motion, in the feature-level. Jeong et al. [39] leverage occlusion consistency in self-supervised optical flow estimation. CSFlow [40] uses cross-strip operations to improve optical flow estimation. OIFlow [41] presents an occlusion-inpainting framework for unsupervised optical flow estimation.

Many studies have been done in these years for unsupervised learning of optical flow, as mentioned above. However, most works focus on the occlusion problem as the occlusion regions are not suitable for image reconstruction. There are seldom works on non-occlusion constraints. In this paper, novel unsupervised losses of optical flow are proposed based on geometric constraints in non-occlusion regions. The pixel coordinate points in the non-occlusion regions are used to calculate these proposed losses: optical flow non-intersection loss and optical flow non-blocking loss, to punish the pixels that do not meet the constraints, which plays a guiding role in the model training.

III. GEOMETRIC PRINCIPLES OF OPTICAL FLOW FIELD IN THE NON-OCCLUSION REGIONS

2D image is a reflection of the real 3D world, and the real motion takes place in 3D space. The 2D optical flow can be obtained by projecting the 3D scene flow to the 2D image plane as in Fig. 1. For the convenience of presentation and explanation, the camera is assumed to be stationary and the occlusion is caused by the motion of observed objects. In Fig. 1(a), at frame $t$, the car and the pedestrian can be seen by the camera, while the nearer car will occlude the farther pedestrian at frame $t + 1$. The pixel coordinate points of the cars and pedestrians at frame $t$ and frame $t + 1$ are visualized on the image plane. The pixel coordinate points of the pedestrian will be surrounded by the pixel coordinate points of the car. For example, the red pixel coordinate point of the pedestrian in Fig. 1(a) is surrounded by four adjacent pixel coordinate points of the car (see the brown square for details), and we call this phenomenon as pixel blocking. Similarly,
Fig. 1. Optical flow intersection and pixel blocking caused by occlusion. Fig. (a) shows the case of occlusion for rigid objects, meanwhile the optical flow intersection and pixel blocking will occur. Fig. (b) shows the case of non-occlusion for flexible objects, meanwhile the optical flow intersection and pixel blocking will not occur.

Fig. 2. An extreme situation that there are intersected flows, but there are no occlusion because of the big motion in consecutive frames.

Fig. 3. An extreme situation that there are blocked pixel coordinate points, but there are not occlusion because of the big motions of multiple objects in consecutive frames.

the pixel coordinate points of the car are also surrounded by the pixel coordinate points of pedestrian. At the same time, the optical flows (the motion vectors of pixel coordinate points) of different objects are intersected when occlusion occurs. Therefore, flow intersection and pixel blocking have a connection with occlusion. Fig. 1(b) presents a non-occlusion flexible and deformable object. It can be seen that some pixel coordinate points have a motion away from the camera in 3D space. There is an aggregated optical flow field but the optical flow is not intersected and the pixel coordinate points are not blocked by surrounding adjacent pixel coordinate points.

From these observations, we infer the principles that the optical flow of one pixel coordinate point will not intersect the optical flow of nearby other pixel coordinate points and the pixel coordinate point will not be blocked by surrounding adjacent pixel coordinate points.

Fig. 4. The overview of our unsupervised learning pipeline of optical flow.

IV. UNSUPERVISED LEARNING OF OPTICAL FLOW BASED ON NON-OCCULTION CONSTRAINTS

A. The Overview of Our Unsupervised Framework of Optical Flow

The overview of our unsupervised learning pipeline of optical flow is shown in Fig. 4. There are two adjacent images $X_t \in \mathbb{R}^{H \times W \times 3}$ and $X_{t+1} \in \mathbb{R}^{H \times W \times 3}$. They are
input to an optical flow estimation network \( f_0 \) to get the forward optical flow \( V_t = f_0(X_t, X_{t+1}) \) and backward optical flow \( V_{t+1} = f_0(X_{t+1}, X_t) \). The \( V_t \) indicates the 2D flow vector from \( X_t \) to \( X_{t+1} \) for each pixel in \( X_t \), while \( V_{t+1} \) indicates the optical flow from \( X_{t+1} \) to \( X_t \). Our objective is to obtain perfect parameters \( \theta \) of the network from image sequences without the ground truth of optical flow to realize the optimized performance of optical flow. Usually the calculation of losses of unsupervised optical flow learning includes both forward and backward directions. Fig. 4 gives the losses in one direction (from \( t \) to \( t+1 \)), and the other direction (from \( t+1 \) to \( t \)) is similar. The consistency of forward and backward optical flow is used to estimate the occlusion regions [13]. Then, the non-occlusion regions are the other parts in the image.

The optical flow connects the images of adjacent frames at the pixel level. The optical flow can be unsupervised trained by measuring the corresponding matching of the pixels between two frames, which is commonly realized through image warping [28], [29]. Firstly, the corresponding coordinates \( \hat{X}_t \) after optical flow are calculated as: \( \hat{[i, j]}^T = [i, j]^T + [u_t, v_t]^T \). Then, the warped image can be obtained by the differentiable bilinear interpolation: \( \hat{X}_t(i, j) = \sum_{i' \in \mathbb{Z}} \sum_{j' \in \mathbb{Z}} w^{i,j}(i, j, i', j') X_t(i', j') \), \( \sum_{i'} w^{i,j} = 1 \). \([\_]\) means rounding up to ceil, and \([\_]\) means rounding down to floor. Then, census loss [14] is used to enforce the consistency of warped image \( \hat{X}_t \) and original image \( X_t \) as shown below:

\[
L_{\text{census}} = \sum_{i} (1 - O_t) \cdot \sigma(\rho(X_t, \hat{X}_t)) \\
+ \sum_{i} (1 - O_{t+1}) \cdot \sigma(\rho(X_{t+1}, \hat{X}_{t+1})),
\]

where \( O_t \) and \( O_{t+1} \) are forward occlusion mask and backward occlusion mask, respectively. \( \sigma(x) = (|x| + \epsilon)^q \) is the robust loss function, where \( \epsilon = 0.01 \), \( q = 0.4 \) [17], [22]. The brightness constancy \( \rho(X_t, \hat{X}_t) \) is used to measure the difference between warped image and original image.

The smooth loss [13] makes the estimated flow smooth according to the pixel gradient of the image. As with most methods, we use first-order [13] and second-order [22] smooth loss. The formula is shown as below:

\[
L_{\text{smooth}}(k) = \frac{1}{N} \sum_j |\nabla^k \hat{V}_t| \cdot \exp\left(-\frac{\mu}{3} \sum_i |\nabla X_t(i)|\right),
\]

where \( \mu \) modulates edge weights based on the color channel \( (i \in \{0, 1, 2\}) \) of \( X_t \) and \( \mu = 150.0 \) expresses the order of smoothness.

The non-intersection loss \( L_{\text{non-inter}} \) and non-blocking \( L_{\text{non-block}} \) loss are proposed in this paper to constraint and regulate optical flow learning inspired by the geometric principles of flow field introduced in Section III. These losses are introduced in Section IV-B and Section IV-C. In addition, we also utilize the idea of distillation learning based on teacher and student models [17], [18]. The loss of distillation learning is represented as \( L_{\text{dist}} \).

In summary, the overall loss function is:

\[
L_{\text{all}} = \alpha_1 L_{\text{census}} + \alpha_2 L_{\text{smooth}}(k) + \alpha_3 L_{\text{non-inter}} \\
+ \alpha_4 L_{\text{non-block}} + \alpha_5 L_{\text{dist}},
\]

where \( \alpha_3 = 0.01 \). As for the setting of \( \alpha_4 \), we follow the method of UFlow [22], which is 0 for the first 50 percent of the training and then increases to a constant.
where $P_{mid}$ is the middle pixel of the basic unit, and $P_i$ corresponds to other pixels adjacent to $P_{mid}$ in the basic unit ($i = 1, 2, \ldots, 8$). $P_{i,j}$ and $P_{mid,j}$ represent the three channel values of the RGB color space corresponding to the pixel points of $P_i$ and $P_{mid}$.

As shown in Fig. 5, $O$ is the intersection point between flow vectors $P_{mid}^t P_{mid}$ and $P_6^t P_6$. Then, $P_{mid}^t O = \lambda P_{mid}^t P_{mid}$ and $P_6^t O = \mu P_6^t P_6$, where the optical flow intersection coefficients $\mu_i$ and $\lambda_i$ represent the ratio of the intersection position to the length of the optical flow vector:

$$
\lambda_i = \frac{1}{\Lambda} \left| \frac{x_i^t - x_{mid}^t - \Delta x_i^t}{y_i^t - y_{mid}^t - \Delta y_i^t} \right|, \\
\mu_i = \frac{1}{\Lambda} \left| \frac{\Delta x_i^t y_{mid}^t - x_{mid}^t \Delta y_i^t}{y_i^t - y_{mid}^t - \Delta y_i^t} \right|, \\
\Lambda = -\Delta x_{mid}^t \Delta y_i^t + \Delta x_i^t \Delta y_{mid}^t. 
$$

where $(x_{mid}^t, y_{mid}^t)$ is the coordinate of the intermediate pixel $P_{mid}^t$ at frame $t$, and $(x_i^t, y_i^t)$ is the coordinate of adjacent pixel $P_i^t$ at frame $t$. $P_{mid}^t P_{mid}^t = (\Delta x_{mid}^t, \Delta y_{mid}^t)$ and $P_i^t P_{mid}^t = (\Delta x_i^t, \Delta y_i^t)$ are the optical flow displacements of the pixel points, $P_{mid}^t$ and $P_i^t$, from frame $t$ to the frame $t + 1$. When $0 < \mu_i, \lambda_i < 1$, $P_{mid}^t P_{mid}^t$ and $P_i^t P_{mid}^t$ will intersect.

The optical flow non-intersection loss $L_k$ of the intermediate pixel relative to all 8 adjacent surrounding pixels in the $k$-th basic unit is calculated as follows:

$$
L_k = \begin{cases} 
\frac{1}{8} \sum_{i=1}^{8} w_i \sigma \left( \exp(-|\lambda_i - \mu_i|^2) \right), & 0 < \mu_i, \lambda_i < 1, \\
0, & \text{otherwise}.
\end{cases} 
$$

$L_k$ is calculated in one basic unit and a total of $(H - 2) \times (W - 2)$ basic units are extracted. Then, $L_{non-inter}$ represents the average non-intersection loss of optical flow for these $(H - 2) \times (W - 2)$ units:

$$
L_{non-inter} = \frac{1}{(H - 2) \times (W - 2)} \sum_{k=1}^{(H-2)\times(W-2)} L_k. 
$$

C. The Non-Blocking Loss

As analysed in Section III, in the non-occlusion area, there will be no pixel blocking when the object is moving. The parallelization technique is also used here similar to Section IV-B.

Taking $4 \times 4$ as the sliding kernel size and 1 as the sliding step size. Fig. 6 shows the schematic diagram of the pixel blocking for a basic unit extracted by the sliding kernel, and the dashed box represents a basic unit extracted by the sliding kernel. With 1 as the sliding step, the sliding kernel moves one pixel right or to the down to extract the next basic unit. Based on this principle, $(H - 3) \times (W - 3)$ basic units with a size of $4 \times 4$ can be extracted from the image at frame $t$ with a size of $H \times W$. Parallelization is used to calculate the extracted $(H - 3) \times (W - 3)$ basic units. In each basic unit, the optical flow non-blocking loss of 12 pixels in the periphery is calculated based on the blocking calculation with the 4 pixels
in the middle. Our proposed method determines and measures how far the surrounding pixels flow into the inside of the quadrilateral composed of 4 pixels in the middle.

Define a basic unit with 4 pixels A, B, C, D in the middle and 12 pixels $P_i$ in the periphery, where $i = 1, 2, \ldots, 12$. The four pixels A, B, C, D in the middle of the basic unit at frame $t$ constitute a quadrilateral $ABCD$ at frame $t + 1$, which can be divided into two triangles by a diagonal line. When the quadrilateral $ABCD$ at the second frame is a convex quadrilateral, according to the selection of different diagonals $AC$ or $BD$ for division, there are two cases where the quadrilateral $ABCD$ contains two triangles. For any of the two division cases, if the peripheral pixels flow into a triangle, it can be inferred that occlusion occurs. (For the sake of brief expression, we classify the points falling on the boundary of the triangle as being within the triangle, because this will not affect the subsequent distance calculation.) As shown in Fig. 6(a), According to the diagonal $AC$, the quadrilateral is divided into triangles $ABC$ and $ACD$. The point $P_i$ flows inside triangle $ABC$.

However, if the quadrilateral $ABCD$ at frame $t + 1$ is a concave quadrilateral, the division case with diagonals $AC$ as shown in Fig. 6(b) is not enough to determine that the pixel $P_3$ falls inside the quadrilateral $ABCD$. If $AC$ is as the diagonal in the calculation progress, the point $P_3$ is simultaneously inside triangles $ABC$ and $ACD$. However, the point $P_3$ is not blocked by the quadrilateral $ABCD$, but this can be judged by using the diagonal $BD$ to divide. According to the diagonal $BD$, the quadrilateral $ABCD$ is divided to triangles $ABD$ and $BCD$, and the point $P_3$ is not inside $ABD$ or $BCD$. Therefore, only the point $P_i$ is inside a triangle both in the two division cases, the pixel blocking occurs for the point $P_i$.

For triangle $ABC$ and point $P_i$, when $BA \times BP$, $\bar{AC} \times \bar{AP}$, $\bar{CB} \times \bar{CP}$ are in the same direction, it can be judged that $P_i$ is within $\overline{ABC}$. In the same way, it can be inferred if $P_i$ is within $\overline{ACD}$, $\overline{ABD}$ and $\overline{BCD}$. The logic expression is as follows:

$$
\Gamma_{ABC} = \left( \frac{x_{\bar{B}A}}{y_{\bar{B}A}} \leq \frac{x_{\bar{B}P}}{y_{\bar{B}P}} \right) \land \left( \frac{x_{\bar{A}C}}{y_{\bar{A}C}} \leq \frac{x_{\bar{A}P}}{y_{\bar{A}P}} \right)
$$

$$
\Gamma_{ACD} = \left( \frac{x_{\bar{C}A}}{y_{\bar{C}A}} \leq \frac{x_{\bar{C}D}}{y_{\bar{C}D}} \right) \land \left( \frac{x_{\bar{A}D}}{y_{\bar{A}D}} \leq \frac{x_{\bar{A}P}}{y_{\bar{A}P}} \right)
$$

$$
\Gamma_{ABD} = \left( \frac{x_{\bar{B}A}}{y_{\bar{B}A}} \leq \frac{x_{\bar{B}D}}{y_{\bar{B}D}} \right) \land \left( \frac{x_{\bar{A}D}}{y_{\bar{A}D}} \leq \frac{x_{\bar{A}P}}{y_{\bar{A}P}} \right)
$$

$$
\Gamma_{BCD} = \left( \frac{x_{\bar{B}C}}{y_{\bar{B}C}} \leq \frac{x_{\bar{B}D}}{y_{\bar{B}D}} \right) \land \left( \frac{x_{\bar{C}D}}{y_{\bar{C}D}} \leq \frac{x_{\bar{C}P}}{y_{\bar{C}P}} \right)
$$

where $\Gamma_{ABC}$, $\Gamma_{ACD}$, $\Gamma_{ABD}$, and $\Gamma_{BCD}$ represent if $P_i$ is in the triangles $ABC$, $ACD$, $ABD$, and $BCD$, respectively. As analysed above, it is inferred that $P_i$ flows into the quadrilateral $ABCD$ when $P_i$ flows at least into a triangle both in the two division cases, that is:

$$
\Gamma_{ABCD} = (\Gamma_{ABC} \lor \Gamma_{ACD}) \land (\Gamma_{ABD} \lor \Gamma_{BCD}).
$$

According to the spatial geometric relationship between the quadrilateral $ABCD$ formed by the intermediate four pixels and each peripheral pixel $P_i$ in a basic unit, the optical flow non-blocking loss $E_i$ of the pixel $P_i$ is defined as:

$$
E_k = \begin{cases} 
\frac{1}{12} \sum_{i=1}^{12} e^\frac{k}{d_i}, & \Gamma_{ABCD} = \text{True} \\
0, & \Gamma_{ABCD} = \text{False}
\end{cases}
$$

where $d_i$ is the minimum distance of $P_i$ to each side of the quadrilateral $ABCD$.

The above is about the loss for a peripheral pixel $P_i$ in a basic unit. There are a total of $(H-3) \times (W-3)$ basic units for the source image, and each unit includes 12 peripheral pixels. The optical flow non-blocking loss of the entire image is as follows:

$$
L_{\text{non-blocking}} = \frac{1}{(H-3) \times (W-3)} \sum_{k=1}^{(H-3) \times (W-3)} E_k.
$$

V. EXPERIMENTS

A. Training and Testing Details

1) Datasets: In order to demonstrate the effectiveness of our proposed method, our model is evaluated on the standard optical flow benchmark datasets: Flying Chairs dataset [9], Sintel dataset [31], and KITTI 2015 dataset [4], [23]. Flying Chairs and Sintel are synthetic datasets, and KITTI is a real
The experiment results training and testing on Sintel and KITTI 2015 datasets. ‘FT’ means that the models of optical flow estimation are supervised by fine-tuning on specific evaluation datasets, which is not conducive to practical application. The results in parentheses are not comparable because its training set contains the evaluation set. “()” means that the results are supervised trained on the evaluation set, and “{}” means that the results are unsupervised trained on the evaluation set. The best results under every evaluation set are marked in bold.

Unpublished results are marked as ‘-’.

| Training method | Method         | Multi-frame | Supervised | EPE on Sintel Clean [31] | EPE on Sintel Final [31] | EPE on KITTI 2015 [4] | ER(%) on KITTI 2015 [4] |
|-----------------|----------------|-------------|------------|--------------------------|--------------------------|------------------------|------------------------|
| Supervised      | FlowNet2-ft [10] | √           |            | (1.45)                  | (4.16)                  | (2.01)                | (2.30)                | (8.61)                  | 11.48                  |
|                 | PWC-Net-ft [29]  | √           |            | (1.70)                  | (3.86)                  | (2.21)                | (5.13)                | (2.16)                  | 9.80                    | 9.60                    |
|                 | SelFlow-ft [18]  | √           |            | (1.68)                  | [3.74]                  | (1.77)                | [4.26]                | (1.18)                  | -                      | 8.42                    |
|                 | VCN-ft [30]      | √           |            | (1.66)                  | (2.81)                  | (2.24)                | (4.40)                | (1.16)                  | (4.10)                  | 6.30                    |
| Supervised      | FlowNet2 [10]    | √           |            | 2.02                    | 3.96                    | 3.14                  | 6.02                  | 9.84                    | -                      | 28.20                   |
|                 | PWC-Net [29]     |            |            | 2.55                    | -                       | 3.93                  | 10.35                 | -                       | 33.67                   | -                      |
|                 | VCN [30]         | √           |            | 2.21                    | -                       | 3.62                  | -                     | 8.36                    | (25.10)                 | -                      |
| Unsupervised    | DSTFlow [12]     |             |            | 6.16                    | 10.41                   | (7.38)                | 11.28                 | 16.79                   | (9.69)                  | 36.00                   | (39.00)                 |
|                 | OAFlow [13]      |             |            | (4.03)                  | 7.95                    | (5.95)                | 9.15                  | (8.88)                  | -                      | -                      | (31.20)                 |
|                 | UnFlow [14]      |             |            | -                       | 6.19                    | 10.21                 | 11.9                  | -                      | 23.27                   | -                      |
|                 | MFOccFlow [16]   | √           |            | (3.89)                  | 7.23                    | (5.52)                | 8.61                  | (6.59)                  | (3.22)                  | -                      | 22.94                   |
|                 | EPIFlow [35]     |             |            | 3.94                    | 7.02                    | 5.08                  | 8.51                  | 5.56                    | 2.56                    | -                      | 16.95                   |
|                 | DDFlow [17]      |             |            | (2.92)                  | 6.18                    | (3.98)                | 7.40                  | (5.72)                  | (2.73)                  | -                      | 14.29                   |
|                 | SelFlow [18]     | √           |            | (2.88)                  | [6.56]                  | [3.87]                | [6.57]                | [4.84]                  | [2.40]                  | -                      | 14.19                   |
|                 | UFlow-test [22]  |             |            | 3.01                    | -                       | 4.09                  | -                     | 2.84                    | 1.96                    | 9.39                    | -                      |
|                 | UFlow-train [22] |             |            | (2.50)                  | 5.21                    | (3.39)                | 6.50                  | (2.71)                  | (1.88)                  | (9.05)                  | 11.13                   |
|                 | Our-test         |             |            | 2.94                    | -                       | 3.87                  | -                     | 2.65                    | 1.90                    | 9.17                    | -                      |
|                 | Our-train        |             |            | (2.47)                  | 4.26                    | (3.57)                | 6.28                  | (2.64)                  | (1.88)                  | (9.13)                  | 10.24                   |

dataset. The Flying Chairs dataset contains a total of 22,872 pairs of images, of which 22,232 pairs are used as the training set and the remaining 640 pairs are used as the test set. For the Sintel dataset, we divide the training set and test set according to the standard classification criteria, where the training set contains 2082 images and the test set contains 1128 images. The training set and test set in KITTI 2015 dataset both contain 200 pairs of images.

2) Training Details: For Sintel, it is common to train on the training set, and report the benchmark performance on the test set, which is included in our experiment. However, the test set does not have the public labels and there is a limit on the number of submissions to the official test set, so to be convenient for our ablation experiments, we also train on the test set and evaluate on the training set. Therefore, there are two trained models for Sintel dataset. One is trained on the training set, the other is trained on the test set. Since the Sintel dataset contains both final and clean parts, they are used both when training the model and separately when evaluating the model, like UFlow [22]. For KITTI 2015, there are two models, like Sintel, trained on the multiview extension and evaluated on the raw KITTI 2015 dataset. Besides, pretraining is a very common method to improve accuracy in both supervised [9], [29] and unsupervised [17], [35] optical flow estimation, so we have a pretraining stage in the training set of Flying Chairs before our formal training on Sintel and KITTI 2015 dataset. In addition, we expect to evaluate the generalization ability of our models on different datasets, so the raw KITTI 2015 dataset is also used to verify the generalization ability of our models trained on Flying Chairs and Sintel dataset. It is expected that our methods can be trained on synthetic datasets and evaluated on real datasets to achieve better generalization performance.

3) Evaluation Metrics and Parameter Settings: As with most previous works, we use End point Error (EPE) and Error Rates (ER) as our evaluation metrics. Our optical flow network structure $f_0$ is based on UFlow [22]. So, in addition to our proposed novel loss functions, other hyperparameters are set with reference to UFlow. All experiments are performed with 1 as the batch size on a single of RTX 2080Ti, based on TensorFlow 2.2.0. The Adam [42] method is used as the optimizing strategy of training, where $\beta_1 = 0.9$, $\beta_2 = 0.999$. In the pretraining stage, the learning rate is a constant, $10^{-4}$. In the training stage, exponential decay is used. The learning rate decays 0.5 times per 200 epochs from $10^{-4}$ to $10^{-8}$.

B. Results

Two series of experiments are conducted. The first group of experiments are trained and evaluated on synthetic and real datasets, respectively. The second group of experiments are trained on different synthetic datasets and evaluated on the real dataset, KITTI 2015 dataset, to verify the generalization ability of our method.

1) Comparison With Other Methods: The quantitative evaluation results on Sintel dataset and KITTI 2015 dataset are shown in Table I, which shows the results of unsupervised and supervised optical flow methods. Compared with MFOccFlow [16], EPIFlow [35], DDFlow [17] and SelFlow [18], our method does not need to use the information of multiple frames but achieves better performance, which depends on our proposed novel constraints in the non-occlusion regions. In addition, SelFlow [18] downloads the raw Sintel movie and...
extracts about 10,000 images, which makes its training data include both the official training set and the test set, while our method only trains on the official training set or test set. UFlow [22] systematically compares and improves occlusion segmentation methods. On the basis of getting the fine non-occlusion regions, we propose a geometry-based unsupervised constraint method for the optical flow in the non-occlusion regions. Compared with UFlow [22], we make better use of the details of the non-occlusion regions and achieve better performance. For KITTI 2015 dataset [4], [23], although the evaluation results on training set are similar to those of UFlow [22], the evaluation result of our model on official testing set are better than that of UFlow, which shows the generalization of our method. Generalization is very important for application in practical scenarios.

2) Generalization Test on Real Dataset: To evaluate the generalization of the model broadly, the models trained on different synthetic datasets will be evaluated on all datasets, and the results are shown in Table II. Compared with PWC-Net [29] (supervised method), our unsupervised results are not as good as that of PWC-Net [29] when trained and tested on the Flying Chairs dataset. However, our generalization
optical flow estimation of the adjacent objects. In addition, our constraints of the adjacent objects are constrained, improving the and blocking of the optical flow. So that the relative movement of the adjacent objects can produce intersection towards to cover occlusion regions. Otherwise, the relative movement between adjacent objects can only be towards the bounds of the car. After the estimation the occlusion mask, the optical flow visualization of UFlow is for comparison. The visualization of occlusion and losses are produced by our model.

Performance outperforms the supervised approach, PWC-Net [29], on both the more complex synthetic data, Sintel, as well as the real dataset, KITTI. When trained on Sintel dataset, our generalization performance on both Flying Chairs and KITTI also outperforms PWC-Net [29]. We use the network structure similar to PWC-Net [29], and our results are not as good as it in the training set, but achieve higher generalization performance in other datasets. It is difficult to obtain the ground truth of optical flow for the real dataset, so our unsupervised method has great practical application ability. DDFlow [17] is a multi-frame approach, and we only use two adjacent frames to achieve better results. After the UFlow [22] segments the occlusion regions, we implement fine geometric constraints of optical flow in the non-occlusion regions to achieve higher generalization performance, which indicates that better use of the essential information of optical flow in the non-occlusion regions can further improve the unsupervised performance of optical flow.

The qualitative results of our method compared with UFlow [22] on Sintel and KITTI 2015 benchmarks are shown in Fig 7. It can be seen that our optical flow estimation is more uniform inside each moving objects, such as machetes, moving people, cars, grass, etc. This is because the optical flow cannot move randomly due to the proposed non-intersection and non-blocking losses inside the objects. Thus, the optical flow inside a single object is kept flexibly consistent for its motion, and the overall smoothness of optical flow for each object is ensured. At the same time, the constraints between adjacent objects also make the estimation of optical flow more accurate, such as the car motion estimation of Fig. 8, our proposed losses constrain the bounds of the car. After the estimation the occlusion mask, the relative movement between adjacent objects can only be towards to cover occlusion regions. Otherwise, the relative movement of the adjacent objects can produce intersection and blocking of the optical flow. So that the relative movements of the adjacent objects are constrained, improving the optical flow estimation of adjacent objects. In addition, our visualized results are also better at detailed movements, such as pedestrian legs and butterfly movements.

We also conduct the computation complexity analysis. Model parameters are 5.57M and floating point operations (FLOPs) are 65.99G. The memory requirement is 2350MiB, and the running time is 0.057s on a 2080Ti.

VI. CONCLUSION

In this paper, the motion regularity of the optical flow in the non-occlusion regions is carefully analyzed, and the geometric constraint principles of the optical flow in the non-occlusion regions are proposed. Two loss functions, non-intersection loss and non-blocking loss, are proposed based on the insight into the motion principles of optical flow in the non-occlusion regions. Their effectiveness has been proved by theoretical analysis and experiments. Optical flow is widely used in visual odometry, target tracking, dynamic segmentation, and other autonomous driving fields. The proposed method has a higher generalization performance on the real dataset, which makes the unsupervised method of optical flow in this paper have good practical application ability. Pixel-level geometric analysis and occlusion analysis are also instructive for depth estimation, visual odometry, depth completion, and scene flow estimation.

Unlike traditional RGB cameras, event cameras [43] are extremely sensitive to moving objects where optical flow usually occurs. Therefore, we believe that the complementarity of the event camera data and RGB camera data can be used to optimize the optical flow network to achieve better performance. This will be our future work.

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Fig. 8. The visualization of the maps of the individual losses. Our proposed loss constrains the bounds of the car. The optical flow visualization of UFlow is for comparison. The visualization of occlusion and losses are produced by our model.
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