LIFE: Lighting Invariant Flow Estimation

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(a) Source Image \hspace{2cm} (b) Target Image \hspace{2cm} (c) Warped Image \hspace{2cm} (d) Blended Image

Figure 1: Image warping with flows predicted by LIFE.

Abstract

We tackle the problem of estimating flow between two images with large lighting variations. Recent learning-based flow estimation frameworks have shown remarkable performance on image pairs with small displacement and constant illuminations, but cannot work well on cases with large viewpoint change and lighting variations because of the lack of pixel-wise flow annotations for such cases. We observe that via the Structure-from-Motion (SfM) techniques, one can easily estimate relative camera poses between image pairs with large viewpoint change and lighting variations. We propose a novel weakly supervised framework LIFE to train a neural network for estimating accurate lighting-invariant flows between image pairs. Sparse correspondences are conventionally established via feature matching with descriptors encoding local image contents. However, local image contents are inevitably ambiguous and error-prone during the cross-image feature matching process, which hinders downstream tasks. We propose to guide feature matching with the flows predicted by LIFE, which addresses the ambiguous matching by utilizing abundant context information in the image pairs. We show that LIFE outperforms previous flow learning frameworks by large margins in challenging scenarios, consistently improves feature matching, and benefits downstream tasks.

1. Introduction

Establishing correspondences between image pairs is a fundamental problem in 3D computer vision, which supports many downstream applications, such as relative pose estimation \cite{27, 51}, visual localization \cite{40}, homography estimation \cite{59, 16}, etc. Pixel-wise dense correspondences further enable image editing \cite{19, 23}, 3D reconstruction \cite{1}, etc. Fully supervised flow estimation methods \cite{47, 10, 48} have achieved satisfactory performance for consecutive frames, which usually have similar lighting conditions and pixel displacements between image pairs are usually limited. In more general scenes, there may exist large viewpoint and illumination changes between pairs of images. However, annotating dense correspondences by humans for flow estimation is infeasible for such scenarios as the number of pixels is quite large. To alleviate the impact of large viewpoint change for flow prediction, there were previous research \cite{38, 49} that synthesizes the second image by applying geometric transformations to an image. Although the accurate dense correspondences with large pixel displacements can be accurately obtained from the geometric transformations in this way, the synthesized images still cannot mimic realistic illumination variations and do not conform to actual geometric transformations.

With the mature Structure-from-Motion (SfM) technology \cite{43}, we can collect images of the same scene from the Internet and accurately estimate their camera poses in a unified coordinate system. Due to the large time span of these
images, the lighting and viewpoint of the images can significantly vary, and their actual variations cannot be easily synthesized via simple image transformations. Based on such image pairs with large illumination variations and ground-truth relative pose transformations, we propose the Lighting Invariant Flow Estimation (LIFE) framework that trains a deep neural network to estimate flow with such image-level weak supervisions.

According to epipolar geometry [55], the fundamental matrix deduced from the relative camera pose constrain each pixel in the source image to correspond to a line, referred to as epipolar line, in the target image. If we select a pixel in the target image as the correspondence, the distance from the pixel to the epipolar line is named epipolar distance and it is expected to be zero, which has been widely used to constrain the searching space of optimization-based optical flow estimation [52, 54]. Besides, once the corresponding pixel is selected, it also corresponds to an epipolar line in the source image, from which we can compute another epipolar distance. The sum of these two distances is the symmetric epipolar distance. DFE [34] introduced it as a loss to learn to estimate the fundamental matrix with given correspondences. Inspired by them, we alternate the learning objective in DFE: via minimizing the symmetric epipolar distance loss, we can train a neural network to estimate dense pixel flows, given an image pair with a given fundamental matrix. Thanks to the adequate training data with different lighting conditions, our LIFE can learn robust feature representations against severe lighting variations.

The proposed symmetric epipolar distance loss only imposes weak constraints on the flow estimation, which allows the predicted flow to slide along the corresponding epipolar line. To improve the accuracy of flow, we synthesize an image from one image in the image pair with geometric transformations. The additional pixel-to-pixel constraint derived from the geometric transformations further complements the symmetric epipolar distance loss and achieves accurate lighting-invariant flow estimation. We present an example that warps an image captured at nighttime to an image captured at daytime via the flows predicted by LIFE (Fig. 1).

Besides dense correspondences, establishing sparse correspondences is also an important vision task, which is usually achieved by extracting salient feature points and matching the points according to descriptors. However, as descriptors of feature points are individually extracted from an image with a limited perception field, descriptors from repeated patterns may be indistinguishable. Feature points with ambiguous descriptors are easily erroneously matched during inference, which raises the outlier ratio and might impact downstream tasks. Guiding feature matching with flows is a common strategy in recent visual odometry [32], which alleviates the descriptor ambiguity and reduces computational complexity. Nonetheless, it is not utilized in other applications such as visual localization as previous methods have difficulties in flow estimation for images with large lighting variations. We propose to improve the sparse feature matching with the flows predicted our proposed LIFE. To our best knowledge, we are the first to explicitly address the lighting variation problem of direct flow prediction with the epipolar constraints as weak supervisions and also make use of lighting-invariant flows to improve feature matching in practical scenarios. With the assist of our LIFE, the inlier ratio of sparse correspondences increases and the accuracy of the follow-up geometric transformation estimation is significantly improved.

In summary, our proposed approach has the following major contributions: (1) We propose a weakly supervised framework LIFE that trains the flow estimation neural network with camera pose transformations and can predict accurate flow in large viewpoint and lighting variation scenarios. (2) We propose to improve the sparse feature matching with our predicted lighting invariant flows, which is able to alleviate the ambiguity of local descriptor matching. (3) Our proposed LIFE outperforms state-of-the-art flow estimation methods in challenging scenes by large margins and improves sparse feature matching performance to assist downstream applications.

2. Related Works

Learning to estimate flow Great efforts have been devoted to estimate flow between image pairs in the past four decades. With the success of deep neural networks, learning-based flow estimation has achieved impressive results. A common optical flow estimation scene is to find pixel correspondences in two consecutive images of a video. Dosovitskiy et al. [5] constructed FlowNet, the first end-to-end trainable CNN for predicting optical flow and trained it on the synthetic FlyingChairs dataset. Since then, a great number of works [12, 35, 46, 47, 10, 11, 61, 48] are proposed for improving the neural network architecture. RAFT [48] achieves the best performance with full supervision in all public optical flow benchmarks by utilizing a multi-scale 4D correlation volume for all pairs of pixels and a recurrent unit iteratively updating the flow estimation. Learning flow estimation requires ground-truth pixel-wise annotations, but it is too expensive in real scenes. Some unsupervised learning [13, 36, 25, 58, 62, 21] frameworks circumvent this requirement by utilizing image warping loss and geometry consistency [58, 62, 21]. However, consecutive images under good lighting conditions is a rather simple case and image warping loss assumes constant illumination. Researchers have recently started to address flow estimation in more challenging scenarios where annotating pixel-wise flow for training becomes even more difficult, such as low-light [60] or foggy [56] images. They address the data problem by image synthesize [60] or domain transforma-
tion [56]. Large viewpoint and illumination transformation will also significantly increase the difficulty of flow estimation. [49, 50, 26, 38] focus on improving the neural network architecture for large viewpoint change. The training data is maintained by applying geometric transformations to images, which is not in line with real scenes. To alleviate the impact from illumination variation, Simon et al. [25] use the ternary census transform [45] to compensate for additive and multiplicative illumination change but it is a simple handcrafted approximation. RANSAC-Flow [44] estimates flow with an off-the-shelf feature extractor and the RANSAC [7, 33] based on multiple homographies, which presents good performance but the resultant flows are restricted by the multiple homographies.

Learning with Epipolar Constraints Correspondences anchored upon the surfaces of rigid objects between two views must obey the geometric transformation according to the relative pose, which is called epipolar constraints. As most contents in images are static and rigid, epipolar constraints are widely employed in traditional optimization-based optical flow [52, 54, 55]. Recently, epipolar constraints are introduced to construct loss functions for learning. Subspace constraint and low-rank constraint [61] are applied in unsupervised optical flow learning. Some local feature learning methods leveraged epipolar constraints to train detectors [57] and descriptors [53]. Ranftl et al. [34] learned to estimate fundamental matrix from given correspondences with the symmetric epipolar distance loss. Reducing the correspondence searching space to a narrow band along the epipolar line [9] is also a common strategy. To our best knowledge, we are the first that directly learn flow by the epipolar geometry, we propose a symmetric epipolar distance (SED). According to the epipolar line [9] is also a common strategy. To our best knowledge, we are the first that directly learn flow by the symmetric epipolar distance loss. Fueled by abundant and various training data maintained from SfM, LIFE is robust to large viewpoint and illumination change.

3. Method

We propose the weakly supervised lighting invariant flow estimation (LIFE) framework, which only requires whole-image camera pose transformations as weak supervisions and shows effectiveness on establishing accurate and dense correspondences between images with significant lighting and viewpoint variations. In this section, we will elaborate the LIFE framework and the LIFE-based sparse correspondences establishment. The neural network architecture of RAFT [48] has been proven successful in learning optical flows but it only learns to predict flows from a source image to a target image. We use RAFT to predict flows in both source-to-target and target-to-source directions with shared parameters as our training losses are applied in both directions. Training data are prepared as image pairs with corresponding fundamental matrices, which can be easily obtained from the Internet and processed by SfM techniques to recover the camera poses. Because of the weak supervisions from whole-image camera poses, we further regularizing the flow learning with cycle consistency and synthetic dense flows. Finally, we show how to establish highly accurate sparse correspondences with the bidirectional flows predicted by LIFE.

3.1. Training Light-invariant Dense Flows from Camera Poses

As camera poses between images with large appearance and geometric variations are easier to acquire than dense flows, our proposed LIFE learns from such camera poses as weak supervisions to predict lighting invariant dense flows.

Symmetric Epipolar Distance (SED) loss. Based on the epipolar geometry, we propose a symmetric epipolar distance (SED) loss to achieve this goal. We compute the fundamental matrix $F$ from $I_A$ to $I_B$ according to their camera intrinsic parameters and relative camera pose. As shown in Fig. 2, $F$ restricts that a pixel location $x \in \mathbb{R}^2$ in image $I_A$ can only be mapped to one of the points on a line $l' = Fx$, referred to as epipolar line in image $I_B$. For each point $x$ in image $I_A$, our network estimates its corresponding point in image $I_B$ as $x' = f_{B \to A}(x)$. If the $A$-to-$B$ flows are ideal, the distance of the corresponding pixel location $x'$ to the epipolar line $l'$, named epipolar distance (ED), shall be zero. Reverse, $x$ is also supposed to lie on the epipolar line $l$ derived from $x'$ in image $I_B$ if the reverse flows are ideal, and the distance from $x$ to the epipolar line $l$ should also be zero. The sum of the two epipolar distances is defined as the symmetric epipolar distance (SED). According to the epipolar geometry, the inverted fundamental matrix equals the transpose of the fundamental matrix, we can therefore compute the SED as

$$SED(x, x', F) = ED(x, x', F) + ED(x', x, F^T).$$ (1)

Given the $A$-to-$B$ dense flows $f_{B \to A}$ predicted by our flow network, we can define the following SED loss to evaluate their accuracies by computing $SED$ for all flows in $f_{B \to A}$.

$$L_{SED} = \sum_{x_i \in S} SED(x_i, f_{B \to A}(x_i), F),$$ (2)
where $S$ is the set containing all pixel locations in $I_A$. Compared with photometric consistency loss used in existing unsupervised flow learning frameworks, which assumes constant lighting conditions, the proposed epipolar distance loss is only determined by the fundamental matrix (or relative camera pose). Therefore, the SED loss works even when there exist significant lighting variations between the two images.

**Cycle consistency regularization.** The cycle loss measuring flows’ cycle consistency $d(x) = ||f_{A\leftrightarrow B}(I_{B\leftrightarrow A}(x)) - x||_2$ is a common regularization term in correspondence learning [39]. However, pixels in occluded regions do not satisfy the cycle consistency assumption and might infer large cycle distance errors to overwhelm the cycle loss. Therefore, making all flows to be cycle consistent would actually hinder the training and generate over-smooth flow fields with degraded performances. Inspired by unsupervised optical flow learning [25, 58], we filter out pixels with too large cycle distance errors and use the cycle loss from the kept pixels.

$$L_{cyc} = \sum_{x_i \in S} 1(d(x_i)) \leq \max\{\alpha, \beta||f_{B\leftrightarrow A}(x_i)||_2\}d(x_i),$$

where $1$ denotes the indicator function. A pixel $x$ whose cycle distance is larger than $\alpha$ and $\beta||f_{B\leftrightarrow A}(x)||_2$ will be filtered in the cycle loss.

**Synthetic dense-flow regularization.** Although the SED loss can work on image pairs of actual scenes with significant lighting and pose variations, it can only provide weak supervision on minimizing the distances from points to their epipolar lines. In other words, as long as the predicted flow aligns points to their epipolar lines in the other image, their SED loss is minimal. However, points’ ground-truth correspondences should also be single points. In order to improve the accuracy of the flow prediction, we propose to regularize the estimated flows with synthetic pixel-to-pixel supervisions. Inspired by Rocco et al. [38], for each image pair, we randomly generate an affine or thin-plate spline transformation $T$ to transform image $I_B$ of the image pair. In this way, we can create a synthesized image $I_{B'}$ and a synthesized image pair $<I_A, I_{B'}>$ (Fig. 3) with accurate dense pixel-to-pixel correspondence ground truth. Given the location of a pixel in $I_B$, we can compute its accurate corresponding location in $I_{B'}$ according to the synthesized geometric transformation $T$, and vice versa via the inverse of the geometric transformation $T^{-1}$. We therefore additionally regularize our flow network with a bidirectional geometric transformation (BiT) loss. The BiT loss supervises the bidirectional flow with accurate pixel-to-pixel dense correspondences, but the image pair has a synthetic image transformation and zero lighting variation,

$$L_{BiT} = \sum_{x_i \in S_B} \max\{\alpha, \beta||f_{B'\leftrightarrow B}(x_i) - T(x_i)||_1\} +$$

$$\sum_{x_i \in S_{B'}} \max\{\alpha, \beta||f_{B\leftrightarrow B'}(x_i) - T^{-1}(x_i)||_1\},$$

where $S_B$ and $S_{B'}$ contain locations of valid pixels in $I_B$ and $I_{B'}$ respectively. For points that might be out of the visible region in the target images, we regard these flow as invalid and filter out them for loss computation.

**The overall loss.** For image $I_B$ and its synthetically transformed version $I_{B'}$, $I_B$ is related to $I_A$ according to their fundamental matrix $F$, while the dense correspondences between $I_B$ and $I_{B'}$ are precisely determined by the synthesized geometric transformation $T$. We apply the SED loss and the cycle loss to the bidirectional flow deduced from $I_A$ and $I_B$, and the BiT loss to the bidirectional flow deduced from $I_B$ and $I_{B'}$ (Fig. 3). The SED loss supervises flows between actual image pairs with natural lighting and viewpoint variation but only provides weak supervision signals. On the contrary, the BiT loss regularizes flow with strict dense correspondences with constant lighting conditions and synthesized image transformation. Unifying the losses of the images can simultaneously mitigate both their drawbacks and contribute to training a robust lighting-invariant flow estimation network.

**3.2. Finding Sparse Correspondences with LIFE**

Dense correspondences can be used in many applications but are not mandatory in whole-image geometric transformation estimation tasks, such as relative pose estimation and homography estimation. In such tasks, we only...
Figure 4: With the flow predicted by LIFE, we find the feature point $b_j$ whose descriptor is the closest to that of $a_i$ in the circle as the corresponding point.

We denote the sets of sparse feature points detected in $I_A$ and $I_B$ by $A$ and $B$, and denote their descriptors by $q^a_i$ and $q^b_j$. For a given query feature point $a_i$, we first calculate its warped point $b'_i = f_{B \rightarrow A}(a_i)$ in $I_B$ according to the predicted flows $f_{B \rightarrow A}$. Inside the circle centered at $b'_i$, we regard the feature point $b_j$ whose descriptor is the closest to that of $a_i$ as the corresponding point (Fig. 4), i.e.,

$$j = \arg \max_j q^a_i q^b_j,$$

$$s.t. \|b_j - b'_i\|_2 \leq r.$$  \hspace{1cm} (4)

$r$ is the radius of the circle, which is set as 5 pixel. In this way, we can try to identify a corresponding feature point $b_j$ in $I_B$ for each $a_i$ in $I_A$, and create a matching feature point set $M_{B \rightarrow A}$ that satisfy the above formula. Reversely, we can use the same strategy to establish a matching point set $M_{A \rightarrow B}$ in the reverse direction from $I_B$ to $I_A$. Given the two matching point sets of the two matching directions, we only keep the final matching point pairs as those survive the cycle consistency check, i.e., $x_i = M_{A \rightarrow B}(M_{B \rightarrow A}(x_i))$

Stage 2. We collect the features that are weeded out in stage 1 and denote them by $A_w$ and $B_w$ according to which image they belong to. More correspondences are tried to be established from them as supplements. Given a feature point $a_i \in A_w$ as a query feature, we directly find the feature point $b_j \in B$ who has the closest descriptor in $I_B$ as its corresponding point. Note that this not equivalent to establishing correspondences between all points $A$ and $B$ with feature descriptors, as $A_w$ and $B_w$ are smaller feature point sets after the stage-1 matching. Similar to stage 1, only the matched point pairs that satisfy the cycle consistency check would eventually be kept. The survived matches are the outcome correspondences in stage 2.

Directly matching local features with descriptors would cause erroneous matches due to the ambiguity of descriptors, which can be corrected by the local match in stage 1 with the guidance of the flows, so the quality of the correspondences highly relies on the flows. Unreliable flows can produce misleading guidance, which may even impact the matching. As LIFE is able to predict accurate flows in challenging scenarios, we can identify more inlier correspondences through this algorithm.

4. Experiments

The core contributions of LIFE are making flow estimation between images with challenging lighting and viewpoint variations practical and addressing the ambiguity problem of sparse feature matching with flows. To demonstrate the effectiveness of LIFE, we compare LIFE with state-of-the-art methods in flow estimation, sparse correspondence establishment, and downstream geometric model estimation. We select R2D2 [37] as the representative local feature for the LIFE-based sparse correspondence identification (LIFE+R2D2). At the end, we perform an ablation study to investigate individual modules and the improvement of LIFE for other local features. More interesting experiments and ablation studies are provided in the supplementary materials and are strongly recommended.

Datasets. The MegaDepth dataset [17] collects images under various viewpoint and lighting conditions of 196 scenes and computes their poses with the SfM technique. We solely train LIFE on MegaDepth with camera poses. The scenes used for evaluation have been excluded from training. The HPatches dataset [3] collects image sequences of different scenes under real condition variation. The image sequences can be divided into two subsets: Viewpoint captures images with increasing viewpoint change but under the same illumination condition; Illumination captures images under increasing illumination but with almost the same...
viewpoint. Each image sequence contains a reference image and 5 source images with increasing variation level. The ground truth homography is provided for all images, so we qualitatively evaluate all the dense correspondences, sparse correspondences, and homography estimation with controlled conditions.

### 4.1. Flow Evaluation

We evaluate our flows on the KITTI 2012 flow (training), KITTI 2015 flow (training) [8], Hpatches [3], RobotCar [24, 15] and MegaDepth datasets [17]. KITTI datasets annotate dense flows between consecutive images, which only have small motion and constant illumination. The KITTI 2015 flow contains more dynamic objects than the KITTI 2012 flow. Hpatches contains image pairs with viewpoint and illumination variations of different levels. The dense correspondences used in evaluation is computed from the provided homography. However, these two datasets have certain limitations. To compare the flow prediction performance in real scenes, we further evaluate LIFE on RobotCar [24, 15] and MegaDepth datasets [17]. Dense correspondence annotations are not available in such challenging scenes with large lighting and viewpoint variations. We therefore evaluate the flow performance on provided sparse correspondences.

#### Dense Flow Estimation on KITTI

We first test flow estimation on the lighting-constant KITTI. We compare LIFE with state-of-the-art unsupervised flow learning methods that are not fine-tuned on KITTI. Following the standard optical flow evaluation protocol, we use the Average Endpoint Error (AEPE) and F1 scores in Tab. 2. LIFE achieves the best performance on the KITTI 2012 flow. Compared with the KITTI 2012 flow, the KITTI 2015 flow contains more dynamic objects. Truong et al. [50] introduced a dynamic training strategy by augmenting images with random independently moving objects from the COCO [18] so they achieve lower AEPE than our LIFE on the KITTI 2015 flow. Nonetheless, LIFE still has smaller F1 error even without the dynamic training strategy. Moreover, the experiments on KITTI can only demonstrate the flow estimation performance on cases of simple lighting-constant consecutive images, while LIFE focuses on addressing flow estimation in challenging lighting- and viewpoint-varying scenarios, which will be demonstrated in the following experiments.

#### Dense Flow Estimation on Hpatches

We compute the AEPE and accuracy of compared methods in Tab. 1 with increasing levels of difficulty (from I to V). As the image pairs in the Illumination subset share the same viewpoint, the ground truth flow is 0 for all pixels, which is too simple. We augment the target images in the Illumination subset with generated homographies, so the ground truth flows are no longer all-zero flows. Here, the accuracy is calculated as the percentage of pixels whose endpoint errors are smaller than 5. CAPS [53] learns dense descriptors for feature matching, which establishes dense correspondences by finding the nearest descriptors. It has low accuracy because it does not utilize context information. RAFT [48] is the state-of-the-art supervisory flow estimation method, which fails as well when encountering difficult cases (II-V). DGC-Net [26] and GLU-Net [49] are trained by synthesized images. LIFE consistently outperforms all previous methods and presents increasing superiority from I to V. In Viewpoint (V) and Illumination (V), which include the most challenging cases, LIFE reduces 63.5% and 61.4% AEPE, and raises 20.4% and 17.1% accuracy. These experiments show the remarkable performance of LIFE in the difficult cases with illumination and viewpoint variations.

#### Sparse Flow Estimation on RobotCar and MegaDepth

These two datasets contain image pairs that correspond to various conditions such as dawn and night. The accuracy of estimating sparse flows are reported in Tab. 3. Following RANSAC-Flow [44], a correspondence is deemed correct if its endpoint error is less than $\epsilon = 1, 3, 5$ pixels. RANSAC-Flow (R-Flow) regularizes flows by RANSAC-based multiple homographies. The images in the MegaDepth are cap-

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### Table 1: Flow on Hpatches. We compare the AEPE/Acc (%). The difficulty gradually increases from I to V.

| Method      | AEPE | F1  | AEPE | F1  |
|-------------|------|-----|------|-----|
| DGC [26]    | 8.50 | 32.28 | 14.97 | 50.98 |
| GLU [49]    | 3.34 | 18.93 | 9.79  | 37.52 |
| GLU+ [50]   | 3.14 | 19.76 | 7.49  | 33.83 |
| GLU-GOC+ [50] | 2.68 | 15.43 | 6.68  | 27.57 |
| UFlow [14]  | -    | 9.40  | -     | -    |
| DDFLOW [20] | 8.27 | -    | 17.26 | -    |
| R-Flow [44] | -    | 12.48 | -     | -    |
| LIFE        | 2.59 | 12.94 | 8.30  | 26.05 |

### Table 2: Generalization of optical flow on KITTI. + denotes that they use the dynamic training strategy.

| Method      | KITTI-2012 | KITTI-2015 |
|-------------|------------|------------|
|              | AEPE | F1  | AEPE | F1  |
| DGC [26]    | -    | -    | 14.97 | 50.98 |
| GLU [49]    | 3.34 | 18.93 | 9.79  | 37.52 |
| GLU+ [50]   | 3.14 | 19.76 | 7.49  | 33.83 |
| GLU-GOC+ [50] | 2.68 | 15.43 | 6.68  | 27.57 |
| UFlow [14]  | -    | 9.40  | -     | -    |
| DDFLOW [20] | 8.27 | -    | 17.26 | -    |
| R-Flow [44] | -    | 12.48 | -     | -    |
| LIFE        | 2.59 | 12.94 | 8.30  | 26.05 |
Figure 5: Sparse correspondence identification on HPatches.

Table 3: Sparse flow evaluation on RobotCar and MegaDepth.

| Method          | RobotCar        | MegaDepth       |
|-----------------|-----------------|-----------------|
|                 | 1               | 3               | 5               | 1               | 3               | 5               |
| S-Flow [19]     | 1.12/8.13/16.45| 8.70/12.19/13.30| 5.55/20.33/34.28|
| DGC [26]        | 1.19/9.35/20.17| 25.2/51.0/56.8  |
| GLU [49]        | 2.16/16.77/33.38| 33.8            |
| GLU-GOC+        | -               | 37.3            |
| R-Flow* [44]    | 2.10/16.07/31.66| 53.47/83.45/86.81|
| LIFE            | 2.30/17.40/34.30| 39.98/76.14/83.14|

Table 4: Relative pose estimation on MegaDepth and homography estimation on HPatches.

| Method          | MegaDepth       |
|-----------------|-----------------|
|                 | easy            | moderate        | hard            | HP  |
| SIFT [22]       | 63.9/25.6/36.5 | 20.8/13.2/24.5 | 90.5            |
| SuperPoint [4]  | 67.2/27.1/38.7 | 24.5/14.1/22.5 | -               |
| HardNet [29]    | 66.3/26.7/39.3 | 22.5/12.3/19.1 | -               |
| D2-Net [6]      | 61.8/23.6/35.2 | 19.1/12.2/19.1 | -               |
| CAPS+SP kpt. [53]| 72.9/30.5/53.5 | 38.1/19.2/38.1 | 90.7            |
| R2D2 [37]       | 69.4/30.3/48.3 | 32.6/17.4/32.6 | 75.7            |
| LIFE+R2D2       | 78.7/33.1/62.7 | 45.8/22.4/45.8 | 91.2            |

4.3. Whole-image Transformation Estimation

In all downstream whole-image transformation estimation tasks, we can see the significant improvement of LIFE+R2D2 based on R2D2, which demonstrates both of the remarkable flow prediction performance of LIFE and the practicability of LIFE-based sparse correspondence identification. We evaluate the LIFE+R2D2 on homography estimation, relative pose estimation, and visual localization.

Homography estimation on HPatches. We use the corner correctness metric introduced by SuperPoint [4], which transforms the four corners of an image respectively using the estimated homography and the ground truth homography, and compute the average pixel error of the transformed four corners. An estimated homography is deemed correct if the average pixel error is less than $\epsilon = 5$ pixels. LIFE improves the accuracy of R2D2 by 15.5% and achieves state-of-the-art performance (Tab. 4).

Relative pose estimation on MegaDepth. We divide the MegaDepth test set into three difficulty levels according to the ground truth relative rotation angle: easy([0°, 15°]), moderate ([15°, 30°]) and hard ([30°, 60°]). We report the rotation/translation accuracy in Tab. 4. The relative pose is deemed correct if the angle deviation of its rotation or translation is less than 10°. LIFE+R2D2 significantly improves R2D2 and outperforms other methods by large margins.

Visual localization in Aachen. We evaluate the visual localization on the challenging Aachen DayNight benchmark [42]. The reference images used to build the SfM map are all taken during daytime while the query images are captured at nighttime. We report the percentage of query images localized within three given translation and rotation thresholds at nighttime (Tab. 5). LIFE+R2D2 improves the localization accuracy at all thresholds and ranks 1st on the
Table 5: Visual localization on Aachen (night).

| Method          | 0.25m, 2° | 0.5m, 5° | 5m, 10° |
|-----------------|-----------|----------|---------|
| SuperPoint [40] | 75.5      | 86.7     | 92.9    |
| D2-Net [6]      | 84.7      | 90.8     | 96.9    |
| SuperGlue [41]  | 86.7      | 93.9     | 100.0   |
| R2D2 [37]       | 80.6      | 90.8     | 96.9    |
| LIFE+R2D2       | 81.6      | 94.9     | 100.0   |

4.4. Ablation study

Training loss ablation. We investigate individual components of our LIFE on KITTI and Hpatches with the AEPE metric. K-12 and K-15 denotes KITTI flow 2012 and KITTI flow 2015. HP-V and HP-I (T) denotes the Viewpoint (trans) subset in Hpatches. We assess the effectiveness of our methods by sequentially adding the proposed training losses. T(B’B) denotes that only supervising the network with the flows in one direction of \( B' \leftarrow B \) from the synthetic geometric transformation \( T \). We can see a significant error reduction from T(B’B) to the BiT loss, which indicates the significance of supervising flow prediction in both directions. The KITTI contains consecutive images that share similar lighting conditions. Compared with the SED loss, training with the BiT loss produces less errors on the KITTI because it can provide pixel-to-pixel ground truth. However, it presents worse performance on the Hpatches because the synthesized image does not change the illumination and is not in line with the actual situations. In contrast, the SED loss works with image pairs captured in real scenes so it achieves less error on the Hpatches. We also test imposing cycle consistency on all flows (denoted by “FC”) and adaptive cycle consistency only on small-error pairs (denoted by “AC”). FC impacts the flow estimation because occluded regions in the image do not satisfy cycle consistency, and AC can improve SED on viewpoint change cases. The final model (SED+BiT+AC) that unifies BiT, SED, and AC in the created image triplets achieves the best performance, which demonstrates the SED loss and the BiT loss mitigate their drawbacks well.

LIFE with different local features. We test LIFE with different local features (denoted by “LIFE+*”), including SIFT, SuperPoint, and R2D2 on Hpatches. As LIFE-based sparse correspondences are computed in two stages, we also report the performance of outcome matches in stage 1 (denoted by “LIFE+* local”), which are calculated with the guidance of flows predicted by LIFE. We report the MMA, feature number, and match number of corresponding methods in Fig. 6. LIFE consistently improves the MMA and increases the match number. LIFE+SIFT local, LIFE+SP local, and LIFE+R2D2 local all achieves remarkable MMA scores and remains similar match number, which demonstrates the superior performance of LIFE. After introducing the matches established in stage 2 (“LIFE+* local” to “LIFE+*”), the match number increases while the MMA scores decreases because the matches calculated in stage 1 are better than these supplemented matches.

5. Conclusion

We have proposed the weakly supervised framework LIFE that learns flow estimation via whole image camera pose transformations, which can predict dense flows between two images with large lighting variations. With the assist of LIFE, we improved the matching of sparse local features, which increased both of the inlier ratio and match number. The derived sparse correspondences also benefited downstream tasks. In this paper, the dense flow prediction and sparse feature matching are loosely coupled for sparse correspondences establishment, which does not maximize the efficiency of information utilization though can directly adopt off-the-shelf sparse features. Integrating both dense and sparse correspondences estimation into a unified neural network will be the future work. Moreover, LIFE can predict remarkable flows in challenging scenarios, which may enable more downstream applications.
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