Unsupervised Generation of Optical Flow Datasets

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Abstract

Dense optical flow ground truths of non-rigid motion for real-world images are not available due to the non-intuitive annotation. Aiming at training optical flow deep networks, we present an unsupervised algorithm to generate optical flow ground truth from real-world videos. The algorithm extracts and matches objects of interest from pairs of images in videos to find initial constraints, and applies as-rigid-as-possible deformation over the objects of interest to obtain dense flow fields. The ground truth correctness is enforced by warping the objects in the first frames using the flow fields. We apply the algorithm on the DAVIS dataset to obtain optical flow ground truths for non-rigid movement of real-world objects, using either ground truth or predicted segmentation. We discuss several methods to increase the optical flow variations in the dataset. Extensive experimental results show that training on non-rigid real motion is beneficial compared to training on rigid synthetic data. Moreover, we show that our pipeline generates training data suitable to train successfully FlowNet-S, PWC-Net, and LiteFlowNet deep networks.

1. Introduction

Optical flow is an important modality in computer vision and is used in different applications such as object tracking [2, 47] and action recognition [15, 38, 40].

Optical flow estimation has gained significant progress with the emergence of convolutional neural networks (CNN) [11, 20, 21, 39]. With the development of CNN’s, there is the growing demand for large scale datasets with ground truth information. However, to obtain optical flow ground truth by means of manual labelling is not trivial. For example, the KITTI datasets [16, 32] are constructed by registering point clouds from 10 consecutive frames. Then, by manual labelling, ambiguous points are removed before projecting the frames back to the image space. While being the largest optical flow datasets available with real world images, only 200 pairs of frames are available, which contains sparse ground truth because of this tedious task of manually labelling.

The data-demanding problem of CNNs can be reduced by applying data augmentation techniques or by the use of synthetic data. A well-known synthetic dataset of optical flow is the MPI-Sintel [9]. Images and annotations are rendered from a computer-generated imagery (CGI) movie called Sintel. The dataset includes different challenges for optical flow estimation such as fast motion, specular reflection, atmospheric effect, defocus and motion blur. Although the dataset serves as a good basis for evaluating or fine-tuning CNNs, the small number of frames (around 2K images) still limits the usability for training CNNs from scratch (without transfer learning).

Therefore, large-scale synthetic datasets like FlyingChairs [11] and FlyingThings3D [29] are proposed. They are based on computer-aided design (CAD) models deformed by affine (rigid) transformations (zooming, rotation, and translation) and projected on randomly transformed backgrounds. The purpose is to simulate moving objects and cameras. These datasets are very useful in training and analyzing optical flow models [28]. However, from the benchmarking results, it can be derived that CNNs trained on highly repetitive or monotonous textures fail to generalize well. Moreover, training with non-rigid movements is important as real (not simulated) objects do not always deform in a rigid manner. Unfortunately, such type of motion (optical flow) is not included in currently available datasets [11, 29] and has largely been ignored so far.

Therefore, in this paper, we present and analyze a new approach to create optical flow (training) data from real-world videos. To the best of our knowledge, this is one of the first attempts to study the effect of optical flow datasets on CNNs (the previous being the work of [28]), and the first one to consider non-rigid deformations and natural textures. The pipeline is based on the rigid square matching algorithm [42] that deforms a 2D image using an as-rigid-as-possible principle [1]. The algorithm allows to generate complex deformations according to physical principles which is employed to compute industrial cartoon image deformation [41]. Then, motion statistics are collected from...
real-world videos by computing correspondences between objects-of-interest. Finally, these motion statistics and their variations are used to deform objects to create optical flow data (see Figure 1). In this way, the proposed method generates large amounts of optical flow data consisting of natural textures and non-rigid movements.

The paper has the following contributions.

• The first approach to generate optical flow data from real videos without the need of manual labelling (unsupervised).
• The method is applicable to any type of video because no prior model is required.
• A large scale optical flow dataset consisting of natural textures and non-rigid motions.
• An extensive analysis of optical flow methods applied on the proposed training datasets.

The algorithms and datasets are made publicly available upon acceptance.

2. Related Work

In this section, an overview of related work is given. We focus on: (1) optical flow methods, (2) optical flow datasets, and (3) data augmentation techniques.

Optical Flow As optical flow estimation is ill-posed problem [5], different priors are proposed to constrain the problem [18, 27]. The priors include the assumption of brightness constancy, local smoothness, and Lambertian surface reflectance [5, 43]. To deal with spatial discontinuities and brightness variations, Black et al. proposes a discontinuity-preservation term within a statistical framework [6]. Strategies based on coarse-to-fine warping [7, 8, 46] are employed to reduce the correspondence search space. EpicFlow [35] proposes an effective way to interpolate sparse matches to dense optical flow used as post-processing [3, 4, 19, 45].

Recently, with the success of CNNs, optical flow estimation is shifted from an energy-optimization to a more data-driven approach. Dosovitskiy et al. [11] proposes FlowNet, a CNN which is trained end-to-end. The networks are extended by Ilg et al. [21] to propose FlowNet2 which achieves state-of-the-art performance.

To circumvent the need for optical flow ground truth, Meister et al. [31] replaces the supervised loss by occlusion-aware bidirectional flow estimation and trains FlowNets in an unsupervised way. Zou et al. [48] employs a similar approach by using a cross-task loss. However, as much as supervised methods are limited by the amount of ground truth data, unsupervised methods are limited by the power of loss functions i.e. their ability to model the problem and the contribution of weights for each component loss [31].

### Table 1. Comparison of optical flow datasets. Only the KITTI datasets provide natural scenes (N). Other datasets are generated synthetically (S), and most of the datasets only contain rigid motion. Our method generates optical flow ground truth from real-world videos.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>S/N</th>
<th>Scene types</th>
<th>#Frames</th>
</tr>
</thead>
<tbody>
<tr>
<td>KITTI 2012 [16]</td>
<td>N</td>
<td>Rigid</td>
<td>194</td>
</tr>
<tr>
<td>KITTI 2015 [32]</td>
<td>N</td>
<td>Rigid</td>
<td>200</td>
</tr>
<tr>
<td>Sintel [9]</td>
<td>S</td>
<td>Non-rigid</td>
<td>1,064</td>
</tr>
<tr>
<td>Monkaa [29]</td>
<td>S</td>
<td>Non-rigid</td>
<td>8,591</td>
</tr>
<tr>
<td>Body flow [34]</td>
<td>S</td>
<td>Non-rigid</td>
<td>100K</td>
</tr>
<tr>
<td>GTAV [36]</td>
<td>S</td>
<td>Non-rigid</td>
<td>250K</td>
</tr>
<tr>
<td>Driving [29]</td>
<td>S</td>
<td>Rigid</td>
<td>4,392</td>
</tr>
<tr>
<td>Virtual KITTI [14]</td>
<td>S</td>
<td>Rigid</td>
<td>21K</td>
</tr>
<tr>
<td>FlyingThings3D [29]</td>
<td>S</td>
<td>Rigid</td>
<td>23K</td>
</tr>
<tr>
<td>SceneNet RGBD [30]</td>
<td>S</td>
<td>Rigid</td>
<td>5M</td>
</tr>
</tbody>
</table>

Hence, these methods require manual parameter tuning for new image domains. Other methods propose ways to apply domain knowledge and classical principles such as spatial pyramid, warping, and cost volumes for faster processing and improving state-of-the-art results. For example, LiteFlowNet [20] with 30 times fewer parameters than those of FlowNet2, and PWC-Net [39] with 17 times fewer parameters.

Datasets Table 1 provides a comparison overview of optical flow datasets. It can be derived that most of the datasets provide optical flow for synthetically generated scenes (S) over naturally captured scenes (N). Only the KITTI datasets [16, 32] provide optical flow for natural scenes. However, the datasets are limited to around 200 frames for car-driving scenes and consist mostly of rigid motion flows.

The first attempt to generate large-scale dataset suitable for training deep learning models is FlyingChairs [11]. Dosovitskiy et al. proposes to use 2D images of chairs rendered from CAD models deformed by an affine transformation. The first frame of a pair is created by randomly positioning multiple chair images on an image background. Then, second frame is generated by warping each object using a flow field generated by the affine model with random parameters. While the parametric model is able to generate as many images as required, the affine model limits the type of motion. In contrast, we propose a novel way to compute non-rigid optical flow fields to generate large amounts of optical flow (training) data.

Related work is the SlowFlow benchmark [22] which contains natural videos with non-rigid motion. The method estimates with high accuracy optical flow for image sequences captured from high-quality cameras (>1440p resolution and >200 fps). However, the requirement of spe-
Generating Image Pairs for Optical Flow

Data Augmentation

Data augmentation is a generic strategy to create more (training) data. This is useful for training CNNs to generate models which generalize accordingly. Data augmentation is used in many computer vision tasks, including image classification [23], image segmentation [26], and depth estimation [13].

A widely used technique for augmenting image data is to perform geometric (such as translation, rotation, and scaling) and color augmentation (such as changing brightness, contrast, gamma, and color). Data augmentation for optical flow networks is first proposed by [11] and studied in detail by [28]. The results show that both color and geometry types of augmentation are complementary and important to improve the performance. Inspired by these data augmentation techniques, we propose methods to increase the diversity of the obtained optical flow data by texture augmentation.

3. Generating Image Pairs for Optical Flow

Figure 1 shows the overview of our pipeline. We generate an optical flow ground truth from a pair of frames $I_1, I_2$ taken from a video sequence. The objects of interest ($I_1, I_2$) are obtained by image segmentation. The correspondences computed by the image matching method are used as constraints for the deformation process which results in a dense flow field $F_{1 \rightarrow 2}$. Due to matching errors, the dense flow field may be noisy. Therefore, the obtained flow field is used to warp the object in the first frame $I_1 \rightarrow I_2$. This ensures the correctness of the ground truth as the generated flow field $F_{1 \rightarrow 2}$ is now the underlining mechanism for the image pair $I_1, I_2$. The final images are obtained by combining objects $I_1, I_2$ with a random background image. The following sections describes each step in detail.

3.1. Image segmentation

To extract the object of interest from the video frames ($I_1$ and $I_2$), image segmentation is used. For illustration purposes, we use the image segmentation provided by DAVIS dataset [33]. However, our pipeline works for any off-the-shelf segmentation algorithm (e.g., Mask R-CNN [17]).

3.2. Image matching

Image matching computes point correspondences between a pair of objects. Deep Matching [44] is used for this purpose. The method is able to provide quasi-dense correspondences which are robust to non-rigid deformations and repetitive textures. Image matching is used to capture the statistics of real world object motion, and subsequently use these to compute dense flow fields.

3.3. Image deformation

Image deformation is applied to obtain a dense flow field $F_{1 \rightarrow 2}$. The deformation process is guided by the point correspondences generated by the image matching process and regularized by minimizing the amount of scaling and shearing factors of the local image regions. To this end, the as-rigid-as-possible method of [12] is taken, which supports large shape deformations while satisfying physical constraints [41, 42].

The image deformation task is formulated as an energy optimization problem over a square lattice on the original object. Let $x_{ij}^0$ be the centroid of the lattice cell $(i, j)$ in the original object, and $c_{ij}$ the desired position (constraint) of the resulting deformation. Pairs $(x_{ij}^0, c_{ij})$ are obtained from the image matching process. We now fit $x_{ij}$, i.e., the centroid after deformation, to adhere to the constraints:

\[ x_{ij} = \frac{x_{ij}^0 + c_{ij}}{2} \]
Figure 2. Top-down left-right of each group: examples of image segments, the obtained point matches, the computed flow and the resulting warped images. Note the significant differences between the second frame (bottom-left) and the warped image (bottom right): the errors in the point matches yield a different dense flow field, which is better represented by the warped object. (Best viewed in color.)

\[ E_{\text{fit}}(i,j) = \sum_{(i,j) \in \mathcal{M}} |x_{ij} - c_{ij}|^2, \]  

where \( \mathcal{M} \) denotes the set point-wise matches.

To regularize the deformation, the objective is to rigidly transform each lattice square, while imposing the constraints of Eq. 1. Therefore, the goal is to find an optimal 2D rotation matrix \( R \in \mathbb{R}^{2 \times 2} \) and a translation vector \( t \in \mathbb{R}^2 \), defined over the vertices of the lattice cell \((i,j)\):

\[ E_{\text{reg}}(i,j) = \sum_{k=1}^{4} w_k \left| R(p_k + t) - q_k \right|^2, \]  

where \( p_k(1 \leq k \leq 4) \) are the vertices of the cell \((i,j)\) with centroid \( x_{ij} \), \( q_k \) is the \( k \)-th vertex of the deformed cell, and \( w_k \) is a weight per vertex which is set to \( w_k = \frac{1}{4} \) for simplicity for all the vertices in the lattice [12].

Wang et al. [42] solves the optimal translation vector \( t \) by setting the partial derivatives with respect to \( t \) in Eq. 2 to zero, yielding:

\[ t = x_{ij} - Rx_{ij}^0. \]  

Substituting \( t \) in Eq. 2 simplifies the regularization term to compute the rotation matrix \( R \), yielding:

\[ E_{\text{reg}}(i,j) = \sum_{(i,j) \in \mathcal{I} \atop k=1}^{4} \sum_{4} w_k \left| R(p_k^0 - x_{ij}^0) - (q_k - x_{ij}) \right|^2 \]

The total energy is the weighted sum of the two terms:

\[ E(i,j) = w_{\text{fit}} E_{\text{fit}}(i,j) + w_{\text{reg}} E_{\text{reg}}(i,j), \]

where we use the default trade-off between data fit (\( w_{\text{fit}} = 10 \)) and regularization (\( w_{\text{reg}} = 0.1 \)) following [12].

From the lattice structures, the dense flow field \( F_{1 \rightarrow 2} \) is computed. Due to errors in the image matching process, the obtained flow field may not exactly correspond to the segmented objects, see Figure 2.

### 3.4. Image warping

The obtained flow field \( F_{1 \rightarrow 2} \) is used to deform the first frame’s object \( I_1 \) to be close to the one in the second frame \( I_2 \) and being physical feasible. To ensure the correctness of the ground truth, the second frame’s object is computed by warping the one in the first frame \( I_1 \) using the obtained flow field, resulting in \( I_2 \), see Figure 2. Because image warping relies on interpolation, it may create artifacts in the case of wrong matching (more details are given in Section 4.1). However, it has been employed for similar purposes in the FlyingChairs dataset [11] (with rigid deformation). The flow field \( F_{1 \rightarrow 2} \) is defined as the ground truth for a pair of frames \( I_1, I_2 \).

### 3.5. Background generation

In the final step of the pipeline, objects \( I_1 \) and \( I_2 \) are projected on different backgrounds to obtain full image frames.
The background images are randomly sampled from a set of 8K images of general scenery obtained from Flickr ² as done in [11]. However, to focus the study in this work on only non-rigid deformations, we do not apply affine transformation to the background images. The similar can be done to promote general purposes. Thus, the backgrounds are static in all the image pairs of our dataset (zero-flow).

4. Optical Flow Variation

Ideally, training data for CNNs should consist of a large variety of samples including different types of textures, motion, and displacements. Mayer et al. [28] shows that for synthetic optical flow, CNNs learn a better model when (a) textures are varied and when (b) the displacement statistics of the train and test set match. To this end, we explore different strategies to increase the variation in texture and displacement.

4.1. Frame Distances

One way to control the variation in displacements is to augment the matching results with a (arbitrary) scaling or rotation operation. However, this causes artifacts in the image appearance and warping method. Therefore, we focus on three different variations.

To increase the variation in the flow displacement, we expand the distance between the pair of frames being used for generating the optical flow. Instead of using a pair of subsequent frames \( I_t \) and \( I_{t+1} \), a pair of frames \( I_t \) and \( I_{t+k} \) is used, with \( 1 \leq k \leq 12 \), where larger frame distances produce larger object displacement as shown in Figure 3. However, larger frame distances comes at the cost of a lower matching accuracy between the objects due to large perspective changes and self-occlusion. This creates artifacts in the warped images (see Figure 4).

4.2. Image Textures

To increase the variation in appearance of the objects, the object \( I_1 \) is re-textured after the deformation phase. The corresponding second frame can be obtained by warping the new image using the flow field obtained from deformation. In this way, a flow field \( F_{1 \rightarrow 2} \) is based on a video sequence with its (original) texture, while the object pairs \( I_1 \) and \( I_2 \) can have different appearance. This allows us to increase the variation in the datasets and steer the appearance variation of topical flow data. Additionally, using re-textured objects disentangles the network from using semantic (class specific) information, rendering it helpful to study the effect of image textures to the performance of a generic optical flow network.

5. Experiments

5.1. Experimental Setup

Datasets Optical flow data is generated by our proposed method using the DAVIS [33] dataset. DAVIS provides video segmentation annotations. The DAVIS dataset contains 6K frames from real videos with 384 segmented objects. A single object per pair of frames is used by taking the union of the segmented objects. We compare the performance of methods trained on the synthetic FlyingChairs dataset [11], which contains 22K image pairs with corresponding flow fields of a chair projected on different backgrounds. In the literature, FlyingChairs is used extensively to train CNNs.

For evaluation, the Sintel [9] dataset is used. Sintel contains large displacement of non-rigid optical flows obtained from the open source 3D film Sintel. A subset of 410 image pairs is used from the train set for evaluating our methods. We also evaluate on the HumanFlow [34] dataset containing non-rigid motion of human bodies. For evaluation, we use

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In this section, we study the effect of appearance and displacement variations in training optical flow fields.

Frame distances In this experiment, we analyze the influence of augmenting the dataset with image pairs taken from larger frame distances, i.e., using a pair of $I^t$ with $I^{t+k}$ for $k \geq 2$, $k = 1$ indicates pairs of consecutive frames. The results are shown in Table 2.

As shown in Figure 3, larger distances cause larger displacements in the training set. Despite the increase of training data, the image appearances basically stay the same as they are extracted from the same set of DAVIS.

From these results, it can be derived that increasing the frame distance is, in general, beneficial. Another observation is that by adding frames with $k > 5$ increases performance marginally on Sintel-val. This could be due to the artifacts introduced by warping interpolation and incorrect matches in large frame distances. As a result, in the following experiments we limit the use of data generation to frame distances from 1 to 5.

Image textures In this section, we extend the appearance variation of the training data by texture augmentation, denoted by R. After obtaining the flow field, the original texture, indicated by O, is replaced by a random image. As an example, the set O1 and R1 are created from consecutive image pairs (the number indicates the frame distance), where the frame pairs in O1 appear with original textures, and R1 with random images. The training set that employs both original and re-textured images is indicated by (O+R).

The images being used for re-texturing include (1) general natural images as used in [11], (2) synthetic images with repetitive patterns (SynR), (3) real images with repetitive patterns (ReaR), and (4) Sintel-val images (SINv). The first set is used to re-texture and improve the variation of training sets R, while the rest is used to test the networks' behaviors in different scenarios. Examples of re-texturing images are shown in Figure 5. All the texture sets are mutually exclusive.

We train FlowNet-S using the training data from O1, O[1-4], R[1-4], and (O+R)[1-4] and evaluate them on 3 sets, namely D1, D5, and Sintel-val. D1, D5 are the same DAVIS data, with frame distance 1 and 5, being re-textured with the images from one of the 3 texture sets SINv, SynR, and ReaR. While D1 contains the frame distance being used in O1 and as a part of O[1-4], R[1-4] and (O+R)[1-4], the D5 group contains larger displacements that have not been seen in any of these sets.

The results are shown Table 3. The average of each column appears in the same order, i.e. SINv, ReaR, SynR (from low to high respectively), applying to both D1 and D5 groups. This shows the dependency of the performance on the test images’ textures. The large gap in performance between D1 and D5 groups indicates the dependency on the test displacement: D1 contains many small displacement compared to D5 and Sintel-val.

There are small increases (0.03 on average) from O1 to O[1-4] in the D1 group compared to those in the D5 group (0.15 on average). Because D1 displacements are the same as those of the O1 set, adding more displacements does not help much in improving performance. Nonetheless, it shows that there is no need to strictly match the distributions of the training and testing sets to achieve the best performance as shown by [28]. As O1 and D1 have the
Table 3. Performance for different texture types. Improvement of R[1-4] and (O+R)[1-4] over O1 is higher than that of O[1-4], even though they share similar displacement distribution, indicating the benefit of training on diversified texture sets.

<table>
<thead>
<tr>
<th>Training set</th>
<th>D1 SINv SynR ReaR</th>
<th>D5 SINv SynR ReaR</th>
<th>Sintel-val</th>
</tr>
</thead>
<tbody>
<tr>
<td>FC</td>
<td>3.13 3.47 3.38</td>
<td>6.28 7.29 6.92</td>
<td>5.10</td>
</tr>
<tr>
<td>O1</td>
<td>2.24 2.52 2.45</td>
<td>4.20 4.82 4.62</td>
<td>5.50</td>
</tr>
<tr>
<td>O[1-4]</td>
<td>2.22 2.55 2.42</td>
<td>4.02 4.75 4.42</td>
<td>5.10</td>
</tr>
<tr>
<td>R[1-4]</td>
<td>2.10 2.43 2.26</td>
<td>3.99 4.61 4.32</td>
<td>4.96</td>
</tr>
<tr>
<td>(O+R)[1-4]</td>
<td><strong>2.05</strong> 2.42 2.23</td>
<td><strong>3.86</strong> 4.60 4.24</td>
<td><strong>4.98</strong></td>
</tr>
</tbody>
</table>

Table 4. Comparison of different segmentation granularities: using the ground truth segmentation provided by DA VIS, the whole image frame, the bounding boxes enclosing the ground truth segmentation, and results from off-the-shelf MaskRCNN. All results are from training with frame distance 1-5.

<table>
<thead>
<tr>
<th>Training set</th>
<th>Sintel-val</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entire frame (F)</td>
<td>5.69</td>
</tr>
<tr>
<td>Box (B)</td>
<td>5.16</td>
</tr>
<tr>
<td>DA VIS (D)</td>
<td>5.06</td>
</tr>
<tr>
<td>Mask RCNN (M)</td>
<td><strong>4.91</strong></td>
</tr>
</tbody>
</table>

same displacement distributions, adding more frame distances can only distort the distribution matching. Instead, we suggest that training sets should contain a wide range of displacement and motion types: methods trained with FlyingChairs data, which contain only affine transformations, under-perform those trained with non-rigid transformations on both seen and unseen displacement groups.

The pair (O[1-4], R[1-4]) shares the same displacement distribution for different texture variations. As the network is exposed to more images during training, it learns better to find correspondences. This provides a higher increase in performance than adding more displacement, i.e. an increase of 0.12 for D1 and 0.09 for D5 on average. This confirms the hypothesis that the network should be trained with a wide variety of textures.

The performance improvement is the most from O[1-4] to (O+R)[1-4]: 0.15 and 0.16 on average for group D1 and D5 respectively. Although (O+R)[1-4] and O[1-4] share the same distributions, which also capture those in the D1 group, the additional variations R[1-4] show to be helpful to find better correspondences.

From the above analysis, it can be derived that although general performance depends on target data displacements, learning with an increased texture variation is important to push the performance potential as deep models can learn better to find correspondences.

Object shapes So far, the segmentation annotation of the DA VIS dataset is used. In this experiment, we explore how different segment shapes affect the quality of the generated data by the proposed pipeline. Specifically, we compare the data generated using DA VIS segmentation with those using (1) the entire image, (2) simple bounding boxes (indicated by Box), and (3) off-the-shelf segmentation method such as Mask RCNN [17]. The segment examples for DA VIS, Box and Mask RCNN are shown on each row of Figure 6 respectively.

For the bounding boxes, we take the boxes enclosing the provided segments of DA VIS. This, in general, increases the segments’ sizes by including background regions while keeping the objects of interest in focus.

For Mask R-CNN [17], we use the pre-trained model provided by the authors, which is trained on the class labels from the MS-COCO [25] datasets, and run prediction on DA VIS image frames. Due to uncertainties in the inference process, the Mask R-CNN segments cover wide regions in the images rather than focusing on the centered objects like DA VIS’ segments and create a large variation in terms of object shapes and sizes.

The results are shown in Table 4. The network trained with data using Mask R-CNN segments outperforms all the others, even the one using ground truth segments. It is because Mask R-CNN segments, in general, are larger and cover more object types in a scene: not only the objects of interest, but also those in the backgrounds. Hence it provides the network with high variations, which proves to be useful for training. Entire-frame deformation has to take into account the constraints from both backgrounds and foreground objects, thus limits the flexibility and variation in the generated flow. Similarly, since backgrounds are mixed with objects, Box data are restricted and contain less variation, despite covering larger image regions.

In conclusion, using Mask R-CNN is an alternative for the oracle segmentation. This enables the use of any video for training optical flow deep networks.

5.3. Comparison to state-of-the-art

We compare different state-of-the-art algorithms for optical flow, namely LiteFlowNet [20] and PWC-Net [39], which are trained on the datasets obtained from our pro-
posed method on DAVIS to the same algorithms trained on FlyingChairs. The results are evaluated on the Sintel datasets, both validation set (Sintel-val) and the benchmark server (Sintel-test), and the HumanFlow datasets. As the displacement statistics are different in the 2 sets, we includes a zero-flow baseline, i.e. when flow is constantly predicted with zero.

As the Sintel movie is created using mostly static scenes and moving characters, to show the performance of the networks on non-rigid (NR) objects, we manually mask out the backgrounds of the images in the Sintel-val set using the ground truth segmentation provided by [9].

The results are shown in Table 5. The networks trained with our dataset generated using off-the-shelf Mask R-CNN segments and original texture at frame distance 1-5 (O[1-5]M) can perform on a par or slightly better than those trained on the FlyingChairs dataset. The performance is similar when the test images are generally evaluated as a whole, yet the results are better when only non-rigid motion being considered. The dataset also shows benefit on FlowNetS architecture, which is known to perform poorly on small displacement data [34]: the performance on Human Flow shows good improvement over the one trained on FlyingChairs which is near to zero-flow.

By including the textures variations, the networks trained with (O+R)[1-5]M outperforms the FlyingChairs on all tests by a large margin, indicating the usefulness of non-rigid motion and textures variations.

\section{5.4. Performance on real world images}

As there are currently no optical flow benchmarks with real-textures and non-rigid motion, we qualitatively show the results of PWC-Net and LiteFlowNet on real world images. Figure 7 shows the optical flow prediction by LiteFlowNet (top) and PWC-Net (bottom) trained with FlyingChairs and our (O+R)[1-5]M on the QUV A repetition dataset [37]. The dataset contains 100 video sequences of repetitive activities in real life, with minor camera motion, and mostly non-rigid object motion. The models trained with our non-rigid flow set capture better the delineation and details of the objects, especially for non-rigid movements of human parts (indicated by the changes of colors).

\section{6. Conclusion}

In this paper, we introduce an unsupervised pipeline to generate a densely annotated optical flow dataset from videos to train supervised deep networks for optical flow.

Extensive experimental results show that optical flow ground truth generated from the DAVIS videos with non-rigid real movements results in adequate optical flow prediction networks. The pipeline can work either with provided video object segmentation, or with running an off-the-shelf object segmentation algorithm like Mask R-CNN. The latter allows to study, in future work, the effect of using more training data with more diverse non-rigid movements, by applying our pipeline on a larger set of source videos.

<table>
<thead>
<tr>
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Table 5. Comparison of FlowNet-S (FNS), PWC-Net (PWC), and LiteFlowNet (LFN) trained on FlyingChairs and on our generated non-rigid optical flow datasets. Zero flow indicates when optical flow is constantly predicted with zero. NR indicates the subset of non-rigid motion. Training deep networks on our datasets outperforms those trained with the FlyingChairs dataset.
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References


A. More examples on optical flow generation

Figure 8 provides additional visualization of the optical flow generated by our unsupervised pipeline. Each group shows the segmented objects $I_1$, $I_2$ with corresponding matches on the left columns, and the generated optical flow $F_{1 \rightarrow 2}$ with the warped images $\hat{I}_2$ on the right column. Note that the generated optical flow $F_{1 \rightarrow 2}$ does not mean to be the ground truth for the pair $(I_1, I_2)$ due to the errors in matching process, but it is for the pair $(I_1, \hat{I}_2)$. Note also the natural appearance of the warped images, although do not exactly fit to the real $I_2$, but capture the object non-rigid movement. The images are taken from the DAVIS benchmark [33] using the provided segments.

B. More qualitative results on real images

We show additional qualitative results on the QUVa repetition dataset [37] for LiteFlowNet [20] on Figure 9 and PWC-Net [39] on Figure 10. For each image, from top to bottom respectively are (1) the RGB images, (2) optical flow prediction from training the corresponding architecture on the FlyingChairs dataset [11], and (3) prediction from that being trained on our (O+R)[1-5]M dataset generated from our unsupervised pipeline. As our dataset focuses on non-rigid movements, the networks can capture better the non-rigid movement in human actions (indicated by the transitions of the flow color), and thus results in more accuracy, better details, and sharper boundaries.
Figure 8. In each group, left column: example of image segments and the obtained point matches for 2 frames $I_1$ and $I_2$; right column: the computed optical flow $F_{1\rightarrow2}$ and the resulting warped image $I_2$. Note the significant differences between the second frame $I_2$ (group left bottom) and the warped image $I_\hat{2}$ (group right bottom): the errors in the point matches yield a different dense flow field, which is better represented by the warped object. (Best viewed in color.)
Figure 9. Qualitative results on QUVA repetition dataset [37] of LiteFlowNet [20] that is trained on FlyingChairs (middle row) and on the (O+R)[1-5]M dataset obtained from DAVIS [33] using our unsupervised optical flow generation pipeline (bottom row). LiteFlowNet trained using our dataset can capture the non-rigid movements of objects in the scenes with better details and delineation. (Best viewed in color.)
Figure 10. Qualitative results on QUVA repetition dataset [37] of PWC-Net [39] that is trained on FlyingChairs (middle row) and on the (O+R)[1-5]M dataset obtained from DAVIS [33] using our unsupervised optical flow generation pipeline (bottom row). PWC-Net trained using our pipeline can capture the non-rigid movements of objects in the scenes (indicated by the transitions of colors) with better details and accuracy. (Best viewed in color.)