Optical Flow Estimation using a Spatial Pyramid Network

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Abstract

We learn to compute optical flow by combining a classical coarse-to-fine flow approach with deep learning. Specifically we adopt a spatial-pyramid formulation to deal with large motions. According to standard practice, we warp one image of a pair at each pyramid level by the current flow estimate and compute an update to the flow field. Instead of the standard minimization of an objective function at each pyramid level, we train a deep neural network at each level to compute the flow update. Unlike the recent FlowNet approach, the networks do not need to deal with large motions; these are dealt with by the pyramid. This has several advantages. First the network is much simpler and much smaller; our Spatial Pyramid Network (SPyNet) is 96% smaller than FlowNet in terms of model parameters. Because it is so small, the method could be made to run on a cell phone or other embedded system. Second, since the flow is assumed to be small at each level (<1 pixel), a convolutional approach applied to pairs of warped images is appropriate. Third, unlike FlowNet, the filters that we learn appear similar to classical spatio-temporal filters, possibly giving insight into how to improve the method further. Our results are more accurate than FlowNet in most cases and suggest a new direction of combining classical flow methods with deep learning.

1. Introduction

Recent years have seen significant progress on the problem of accurately estimating optical flow, as evidenced by improving performance on increasingly challenging benchmarks. Despite this, most flow methods are derived from a "classical formulation" that makes a variety of assumptions about the image, from brightness constancy to spatial smoothness. These assumptions are only coarse approximations to reality and this likely limits performance. The recent history of the field has focused on improving these assumptions or making them more robust to violations. This has led to steady but incremental progress.

An alternative approach would be to abandon the classical formulation altogether and start over using recent neural network architectures. Such an approach takes a pair (or sequence) of images and learns to directly compute flow from them. Ideally such a network would learn to solve the correspondence problem (short and long range), learn filters relevant to the problem, learn what is constant in the sequence, and learn about the spatial structure of the flow and how it relates to the image structure. The first attempts are promising but do not yet beat the classical methods in terms of flow accuracy on standard benchmarks.

Goal. We argue that there is an alternative approach that combines the best of both approaches. Decades of research on flow has produced well engineered systems and several principles that are well understood and effective. But there are places where these methods make assumptions that limit their performance. Consequently, here we apply machine learning to address the weak points, while keeping the engineered architecture, with the goal of 1) improving performance over existing neural networks and the classical methods upon which our work is based; 2) achieving real-time flow estimates with accuracy better than the much slower classical methods; and 3) reducing memory requirements to make flow more practical for embedded, robotic, and mobile applications.

Problem. The key problem with recent methods for learning flow [15] is that they typically take two frames, stack them together, and apply a convolutional network architecture. When the motions between frames are larger than one (or a few) pixels, spatio-temporal convolutional filters will not obtain meaningful responses. Said another way, if a convolutional window in one image does not overlap with related image pixels at the next time instant, no meaningful temporal filter can be learned.

There are two problems that need to be solved. One is to solve for long-range correlations while the other is to solve for detailed, sub-pixel, optical flow and precise motion boundaries. FlowNet [15] attempts to learn both of these at once. In contrast, we tackle the latter using deep learning and rely on existing methods to solve the former.

Approach. To deal with large motions we adopt a traditional coarse-to-fine approach using a spatial pyramid[1]. At that top level of the pyramid, the hope is that the motions between frames are smaller than a few pixels and that, consequently, the convolutional filters can learn meaningful temporal structure. At each level of the pyramid we solve for the flow using a convolutional network and up-sample the flow to the next pyramid level. As is standard, with classical formulations [38], we warp one image towards the other using the current flow, and repeat this process at each pyramid level. Instead of minimizing a classical objective function at each level, we learn a convolutional network to predict the *flow increment* at that level. We train the network from coarse to fine to learn the flow correction at each level and add this to the flow output of the network above. The idea is that the displacements are then always less than a few pixels at each pyramid level.

This approach means that, at any pyramid level, the network has a simpler task than predicting a wide range of motions for the full-scale images. As a result, at each level we can use a much smaller network than used in FlowNet [15]. Here we use a network with only 5 layers, which we found to be sufficient. The total size of all networks is 96% smaller than FlowNet, meaning that it runs faster, and uses much less memory.

We call the method *SPyNet*, for Spatial Pyramid Network, and train it using the same data as FlowNet [15]. Specifically we use the Flying Chairs dataset in [15]. We report similar performance as FlowNet on Flying Chairs, Sintel [10] and KITTI [17], outperforming them by a small margin in most cases. We are significantly more accurate than FlowNet on the Middlebury [4] dataset.

An advantage of SPyNet over traditional approaches is its computational efficiency. The expensive iterative propagation of spatial coherence constraints is replaced by the non-iterative computation of the neural network.

We are not claiming to solve the full optical flow problem with SPyNet – we address the same problem as traditional approaches and inherit some of their limitations. For example, it is well known that large motions of small or thin objects are difficult to capture with a pyramid representation. We see the large motion problem as separate, requiring different solutions. Rather, what we show is that the traditional problem can be reformulated, portions of it can be learned, and performance improves in many scenarios.

Additionally, because our approach connects past methods with new tools, it provides insights into how to move forward. In particular, we find that SPyNet learns spatio-temporal convolutional filters that resemble traditional spatio-temporal derivative or Gabor filters [2, 22]. The learned filters resemble biological models of motion processing filters in MT and V1 [37]. This is in contrast to the highly random-looking filters learned by FlowNet. This suggests that it is timely to reexamine older spatio-temporal filtering approaches with new tools.

In summary our contributions are: 1) the combination of traditional coarse-to-fine pyramid methods with deep learning for optical flow estimation; 2) a new SPyNet model that is 96% smaller and significantly faster than FlowNet; 3) SPyNet achieves comparable or lower error than FlowNet on standard benchmarks – Sintel and Middlebury; 4) we evaluate the choice of network architecture; 5) learned spatio-temporal filters that provide insight about what filters are needed for flow estimation; 6) the trained network and related code will be made publicly available for research purposes.

2. Related Work

Our formulation effectively combines ideas from "classical" optical flow and recent deep learning methods. Our review focuses on the work most relevant to this.

Spatial pyramids and the "classical" approach. The "classical" formulation of the optical flow problem dates to Horn and Schunck [23] and involves optimizing the sum of a data term based on brightness constancy and a spatial smoothness term. The classical methods typically suffer from the fact that they make very approximate assumptions about the image brightness change and the spatial structure of the flow. Many methods have attempted to make these methods more robust by changing the assumptions. A full review would effectively cover the history of the field and consequently we refer the reader to Sun et al. [38] for an overview of classical methods. The key advantage of learning to compute flow, as we do here, is that we do not hand craft changes in these assumptions. Rather, the variation in image brightness and spatial smoothness are embodied in the learned network.

The idea of using a spatial pyramid has a similarly long history dating to [9] with its first use in the classical flow formulation appearing in [18]. Typically Gaussian or Laplacian pyramids are used for flow estimation with the primary motivation to deal with large motions. Typical gradient-based optical flow estimation relies on the computation of spatial and temporal derivatives of the image sequence, implemented as filters [24]. This formulation assumes that the image motion is small. Through spatial smoothing and subsampling, this small motion assumption holds at high levels of the pyramid. A coarse-to-fine approach then estimates the flow such that, at each pyramid level, the motion is updated with an estimate that is assumed to be small.

These methods are well known to have problems when small objects move quickly. To deal with this Brox et al. [7] incorporate long range matching into the traditional optical flow objective function. This approach of combining image matching to capture large motions, with a variational

[1]This, of course, has well-known limitations, which we discuss later.

method for fine motions, can produce accurate results [32]. Alternatively, Sevilla et al. [36], replace the classical pyramid with a channel representation in which the spatial pyramid is effectively applied to segmented images, preserving small structures at high levels of the pyramid.

Of course spatial pyramids are widely used in other areas of computer vision and have recently been used in deep neural networks [14] to learn generative image models.

Spatio temporal filters. Burt and Adelson [2] lay out the theory of spatio-temporal models for motion estimation and Heeger [22] provides a computational embodiment. While inspired by human perception, such methods did not perform well at the time [6].

Various methods have shown that spatio-temporal filters emerge from learning, for example using independent component analysis [44], sparseness [31], and multi-layer models [11]. Memisevic and Hinton learn simple spatial transformations with a restricted Boltzmann machine [30], finding a variety of filters. Taylor et al. [42] use synthetic data to learn "flow like" features using a restricted Boltzmann machine but do not evaluate flow accuracy. Han et al. [19] propose a rich set of filters for representing a "video primal sketch" but do not learn the filters or use them for estimating optical flow.

Dosovitskiy et al. [15] learn spatio-temporal filters for flow estimation using a deep neural network, yet these filters do not resemble classical filters inspired by neuroscience. By using a pyramid approach, here we learn filters that are visually similar to classical spatio-temporal filters, yet because they are learned from data, produce good flow estimates.

Learning to model and compute flow. Possibly the first attempt to learn a model of optical flow is the work of Freeman et al. [16]. They consider a simple synthetic world of uniform moving blobs with ground truth flow. They vector quantize training patches and compute neighborhood co-occurrence statistics. In an MRF, they perform belief propagation to estimate flow using the learned model. The training data was not realistic and they did not apply the method to real image sequences.

Roth and Black [33] learn a field-of-experts (FoE) model to capture the spatial statistics of optical flow. The FoE can be viewed as a (shallow) convolutional neural network. The model is trained this using flow fields generated from laser scans of real scenes and natural camera motions. They have no images of the scenes (only their flow) and consequently the method only learns the spatial component of the problem.

Sun et al. [13] describe the first fully learned model that can be considered a shallow convolutional neural network. They formulate a classical flow problem with a data term and a spatial term. The spatial term uses the FoE model from [33], while the data term replaces traditional derivative filters with a set of convolutional image filters that are learned from data. While the method improved over the baseline, with limited training data and a small set of filters, it did not fully show the promise of learning for flow estimation.

Wulff and Black [47] take a different approach to learning the spatial statistics of optical flow. They take real (noisy) optical flow computed from natural movies and use robust PCA [20] to learn a global flow basis. While overly smooth, they show that such a global model can be used to compute reasonable flow relatively quickly.

Deep Learning. The above learning methods suffer from limited training data and the use of shallow models. In contrast, deep convolutional neural networks have emerged as a powerful class of models for solving recognition [21, 41] and dense estimation [12, 27] problems in computer vision. However, the such methods have been less successful for estimating optical flow.

FlowNet [15] represents the first deep convolutional architecture for flow estimation that is trained end-to-end. The network shows promising results, despite being trained on an artificial dataset of chairs flying over randomly selected images. Despite promising results, the method lags behind the state of the art in terms of accuracy [15]. It remains an open question as to which deep architectures are most appropriate for the problem and how best to train these.

Recent works attempt to learn to compute flow in an unsupervised or semi-supervised fashion. Such methods have not yet achieved good flow accuracy. For example, Mathieu et al. [29] train a convolutional network to predict future video frames from past ones. The theory is that, if the network is good at this task, it must have learned how to compute optical flow. The model is tested, however, only on frame prediction and not on optical flow estimation.

Tran et al. [43], use the output of a traditional flow method to provide "semi-truth" training data for their 3D convolutional network. The performance is below the state of the art and the method is not tested on the standard benchmark test sets. There have also been several attempts at estimating optical flow using unsupervised learning [3, 48]. However these methods have lower accuracy on standard benchmarks.

Fast flow. Several recent methods attempt to balance speed and accuracy, with the goal of real-time processing and reasonable (though not top) accuracy. GPU-flow [46] began this trend but several methods now outperform it. PCA-Flow [47] runs on a CPU, is slower than frame rate, and produces overly smooth flow fields. EPPM [5] achieves

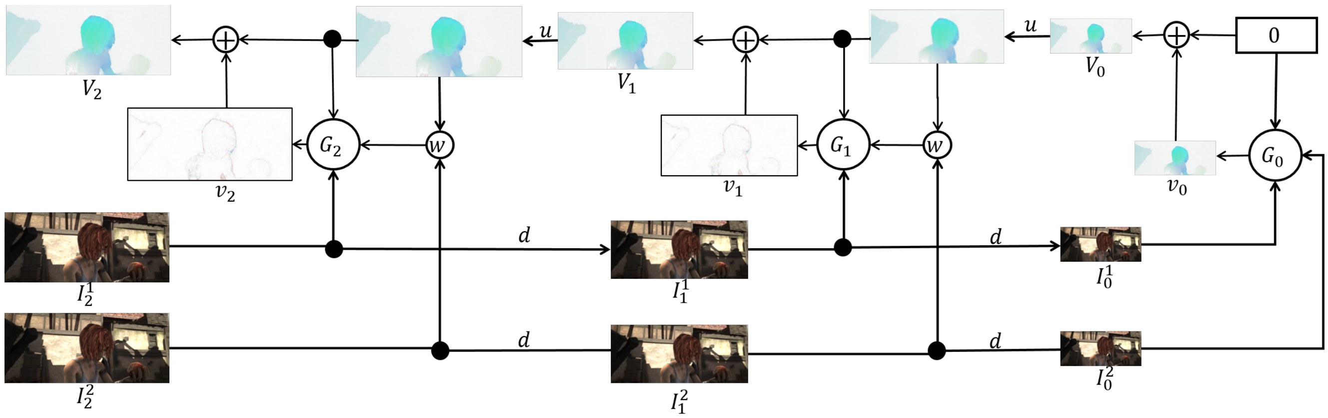

Figure 1. Inference in a 3-Level Pyramid Network [14]: The network G_0 computes the residual flow v_0 at the highest level of the pyramid (smallest image) using the low resolution images $\{I_0^1, I_0^2\}$. At each pyramid level, the network G_k computes a residual flow v_k which propagates to each of the next lower levels of the pyramid in turn, to finally obtain the flow V_2 at the highest resolution.

similar, middle-of-the-pack, performance on Sintel (test), with similar speed on a GPU. Most recently DIS-Fast [26] is a GPU method that is significantly faster than previous methods but is also significantly less accurate.

In contrast, our method is significantly more accurate than all the previous "fast" methods. CNN methods have an advantage over traditional variational methods in that they do not perform iterative optimization to propagate information spatially. Our method is also significantly faster than the best previous CNN flow method (FlowNet), which reports a runtime of 80ms/frame for FlowNetS. The key to our speed is to create a small neural network that fits entirely on the GPU. Additionally all our pyramid operations are implemented on the GPU.

Size is an important issue that has not attracted as much attention as speed. For optical flow to exist on embedded processors, aerial vehicles, phones, etc., the algorithm needs a small memory footprint. Our network is 96% smaller than FlowNetS and takes up only 9.7 MB for storing model parameters, making it easily small enough to fit on a mobile phone GPU.

3. Spatial Pyramid Network

Our approach uses the coarse-to-fine spatial pyramid structure of [14] to learn residual flow at each pyramid level. In the rest of the section, we describe our network and training procedure while summarizing the spatial pyramid structure of [14].

3.1. Spatial Sampling

Let $d(.)$ be the downsampling function that decimates an $m \times n$ image I to the corresponding image $d(I)$ of size $m/2 \times n/2$. Let $u(.)$ be the reverse operation that upsamples images. These operators are also used for downsampling and upsampling the horizontal and vertical components of the optical flow field, V. We also define a warping operator $w(I, V)$ that warps the image, I according to the flow field, V, using bi-linear interpolation.

3.2. Inference

Let $\{G_0, ..., G_K\}$ denote a set of trained convolutional neural network (convnet) models, each of which computes residual flow, v_k

$$v_k = G_k(I_k^1, w(I_k^2, u(V_{k-1})), u(V_{k-1})) \tag{1}$$

at the k-th pyramid level. The convnet G_k computes the residual flow v_k using the upsampled flow from the previous pyramid level, V_{k-1}, and the frames $\{I_k^1, I_k^2\}$ at level k. The second frame I_k^2 is warped using the flow as $w(I_k^2, u(V_{k-1}))$ before feeding it to the convnet G_k. The flow, V_k at the k-th pyramid level is then

$$V_k = u(V_{k-1}) + v_k. \tag{2}$$

As shown in Fig. 1, we start with downsampled images $\{I_0^1, I_0^2\}$ and an initial flow estimate that is zero everywhere to compute the residual flow $v_0 = V_0$ at the top of the pyramid. We upsample the resulting flow, $u(V_0)$, and pass it to the network G_1 along with $\{I_1^1, w(I_1^2, u(V_0))\}$ to compute the residual flow v_1. At each pyramid level, we compute the flow V_k using Equation (2). The flow V_k is similarly propagated to higher resolution layers of the pyramid until we obtain the flow V_K at full resolution. Figure 1 shows the working of our approach using a 3-level pyramid. In practice, we use a 5-level pyramid ($K = 4$).

3.3. Training

We train each of the convnets $\{G_0, ..., G_K\}$ independently and sequentially to compute the residual flow v_k

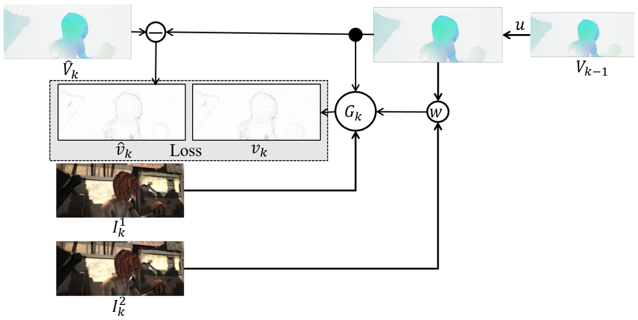

Figure 2. Training Architecture: Training of network G_k requires trained models $\{G_0...G_{k-1}\}$ to obtain the initial flow $u(V_{k-1})$. We obtain ground truth residual flows $\hat{v}_k$ by subtracting downsampled ground truth flow V_k and $u(V_{k-1})$ to train the network G_k using the EPE loss.

given the inputs $\{I_k^1, w(I_k^2, u(V_{k-1})), u(V_{k-1})\}$. We compute target residual flows $\hat{v}_k$ as a difference of target flow V_k at the k-th pyramid level and the upsampled flow, $u(V_{k-1})$ obtained from the trained convnet of the previous level

$$\hat{v}_k = \hat{V}_k - u(V_{k-1}). \tag{3}$$

As shown in Fig. 2, we train each of the networks, G_k, to minimize the average End Point Error (EPE) loss on the residual flow v_k.

3.4. Network Architecture

Each level in the pyramid has a simplified task relative to the full optical flow estimation problem; it only has to estimate a small-motion update to an existing flow field. Consequently each network can be relatively simple. Here, each G_k has 5 convolutional layers. Each convolutional layer is followed by a Rectified Linear Unit (ReLU), except the last one. We use a 7x7 convolutional kernel for each of the layers. The number of feature maps in each convnet, G_k are {32, 64, 32, 16, 2}. The image I_k^1 and the warped image $w(I_k^2, u(V_{k-1}))$ have 3 channels each (RGB). The upsampled flow $u(V_{k-1})$ is 2 channel (horizontal and vertical). We stack image frames together with upsampled flow to form an 8 channel input to the network. The output is 2 channel flow corresponding to velocity in x and y directions.

We found five layers to be optimal during our experiments, producing the best combination of accuracy, size, and speed. Using fewer layers reduced accuracy, while using more did not produce improvements significant enough to justify the increased memory and run time.

3.5. Implementation Details

We train five networks $\{G_0, ..., G_4\}$ such that each network G_k uses the previous network G_{k-1} as initialization. The networks are trained using Adam [25] optimization

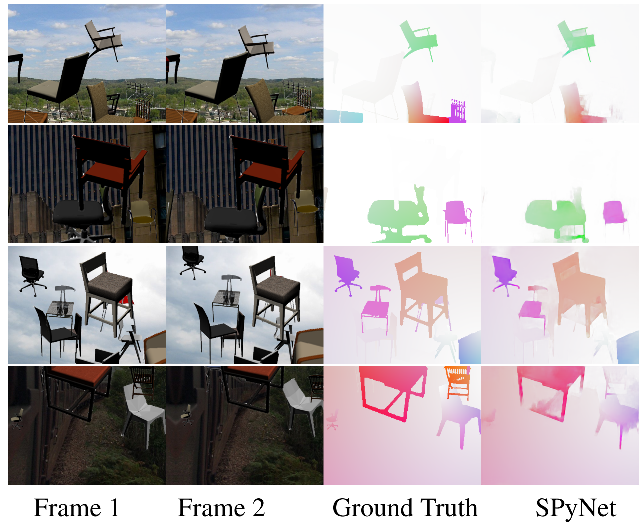

Figure 3. Visualization of optical flow estimates using our model (SPyNet) and the corresponding ground truth flow fields on the Flying Chairs dataset.

with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We use a batch size of 32 across all networks with 4000 iterations per epoch. We use a learning rate of 1e-4 for the first 60 epochs and decrease it to 1e-5 until the networks converge. We use Torch7[2] as our deep learning framework. We use the Flying Chairs [15] dataset and the MPI Sintel [10] for training our network. All our networks are trained on a single Nvidia K80 GPU.

4. Experiments

We evaluate our performance on standard optical flow benchmarks and compare with the previous end-to-end deep learning model for flow estimation, FlowNet [15]. We show better performance than FlowNet on most standard benchmarks with a 96% reduction in model parameters. We also compare with Classic+NLP, which is a traditional pyramid-based method and show significantly improved performance in most cases, while being three orders of magnitude faster.

We compare performance using average end point errors in Table 1. We evaluate on all the standard benchmarks and find that SPyNet is the most accurate in 5 of the categories tested, FlowNetS is most accurate in 3, and FlowNetC is most accurate in 1. Additionally SPyNet is faster than all other methods.

Note that the FlowNet results reported on the MPI-Sintel site are for a version that applies variational refinement ("+v") to the convnet results. Here we are not interested in the variational component, which could be additionally applied ot the output of any convnet with similar results.

[2] http://torch.ch/

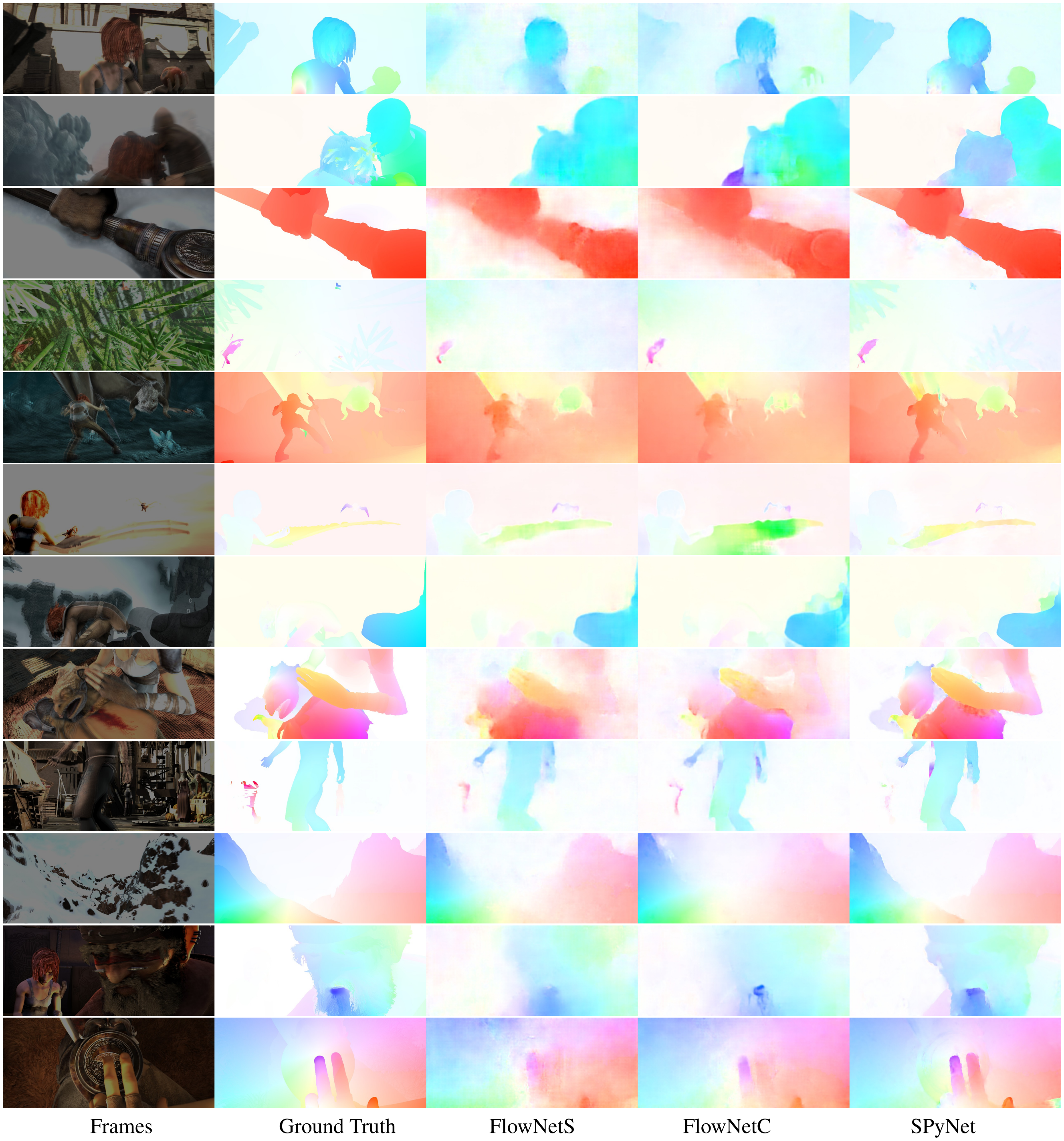

Figure 4. Visual comparison of optical flow estimates using our SPyNet model with FlowNet on the MPI Sintel dataset. The top six rows are from the Sintel Final set and the bottom six row are from the Sintel Clean set. SPyNet performs particularly well when the motions are relatively small.

Consequently, here we compare only on results of the convnet output.

4.1. Flying Chairs

We train five convnets $\{G_0, ..., G_4\}$ at different resolutions of the Flying Chairs dataset. The network G_0 is

Method	Sintel Clean		Sintel Final		KITTI		Middlebury		Flying Chairs	Time (s)
	train	test	train	test	train	test	train	test	test	
Classic+NLP	4.13	6.73	5.90	8.29	-	-	0.22	0.32	3.93	102
FlowNetS	4.50	7.42	**5.45**	**8.43**	**8.26**	-	1.09	-	2.71	0.080
FlowNetC	4.31	7.28	5.87	8.81	9.35	-	1.15	-	**2.19**	0.150
SPyNet	**4.12**	**6.69**	5.57	**8.43**	9.12	-	**0.33**	**0.58**	2.63	**0.069**
FlowNetS+ft	3.66	6.96	4.44	**7.76**	**7.52**	**9.1**	0.98	-	3.04	0.080
FlowNetC+ft	3.78	6.85	5.28	8.51	8.79	-	0.93		**2.27**	0.150
SPyNet+ft	**3.17**	**6.64**	**4.32**	8.36	8.25	10.1	**0.33**	**0.58**	3.07	**0.069**

Table 1. Comparison of average end point errors (EPE) with other methods. Results are divided into methods trained with (+ft) and without fine tuning. Bold font indicates the most accurate results among the neural network methods. All times are measured on the Flying Chairs dataset excluding image loading time.

Method	Sintel Final						Sintel Clean					
	$d_{0\text{-}10}$	$d_{10\text{-}60}$	$d_{60\text{-}140}$	$s_{0\text{-}10}$	$s_{10\text{-}40}$	s_{40+}	$d_{0\text{-}10}$	$d_{10\text{-}60}$	$d_{60\text{-}140}$	$s_{0\text{-}10}$	$s_{10\text{-}40}$	s_{40+}
FlowNetS+ft	7.25	4.61	**2.99**	1.87	5.83	43.24	5.99	3.56	2.19	1.42	3.81	40.10
FlowNetC+ft	7.19	4.62	3.30	2.30	6.17	**40.78**	5.57	3.18	1.99	1.62	3.97	**33.37**
SpyNet+ft	**6.69**	**4.37**	3.29	**1.39**	**5.53**	49.71	**5.50**	**3.12**	**1.71**	**0.83**	**3.343**	43.44

Table 2. Comparison of FlowNet and SpyNet on Sintel benchmarks for different velocities, s and displacement, d of regions from object boundary.

trained with 24x32 images. We double the resolution at each of the upper levels and finally train the convnet, G_4 with a resolution of 384x512.

Data Augmentation We include data augmentation of various sorts while training. We randomly scale images by a factor of $[1, 2]$. We sample rotations uniformly at random within $[-17°, 17°]$. We then apply a random crop to match the resolution of the convnet, G_k being trained. We include additive white Gaussian noise sampled uniformly from $\mathcal{N}(0, 0.1)$. We apply color jitter with additive brightness, contrast and saturation sampled from a Gaussian, $\mathcal{N}(0, 0.4)$. We finally normalize the images using a mean and standard deviation computed from a large sample of Imagenet [34] data in [21].

Fine Tuning To compare with fine-tuned FlowNet, we also evaluate our model with fine tuning. The fine-tuned models are listed as "+ft" in Table 1. Once the convnets G_k are trained, we fine tune the network using the same Flying Chairs dataset but without any data augmentation at a learning rate of 1e-6. We see an improvement of EPE by 0.14 on the test set. Our model achieves better performance than FlowNetS [15] on the Flying Chairs dataset, however FlowNetC[15] performs better than ours. We show the qualitative results on Flying Chairs dataset in Fig. 3.

4.2. MPI-Sintel

We evaluate the performance of our model on MPI-Sintel [10] in two different ways. First, we directly use the model trained on Flying Chairs dataset and evaluate our performance on both the training and the test sets. The resolution of Sintel images is 436x1024. We scale the images to 448x1024, and use 6 pyramid levels to compute the optical flow. The networks used on each pyramid level are $\{G_0, G_1, G_2, G_3, G_4, G_4\}$. We repeat the network G_4 at the sixth level of pyramid for experiments on Sintel. Because Sintel has extremely large motions, we found that this gives better performance than using just five levels.

Then, we extract a validation set from the Sintel training set, using the same partition as [15]. We fine tune our model independently on the Sintel Clean and Sintel Final split, and evaluate the EPE. We show the qualitative results on MPI-Sintel in Fig. 4.

Table 2 compares our fine-tuned model with FlowNet [15] for different velocities and distances from motion boundaries. We observe that we are better than FlowNet for all velocity ranges except the largest displacements. Our model suffers in large displacement regions over 40 pixels. SPyNet is also more accurate at all distances from motion boundaries except when greater than 60 pixels away.

4.3. KITTI and Middlebury

The KITTI [17] and Middlebury [4] datasets are too small for training or fine tuning. For these datasets, we evaluate the results with our model, SPyNet, trained with Flying Chairs. We also evaluate the performance with SPyNet+ft which is fine-tuned on the Sintel-Final dataset.

SPyNet is less accurate than FlowNet (with and without fine tuning) on KITTI. We suspect that more training data

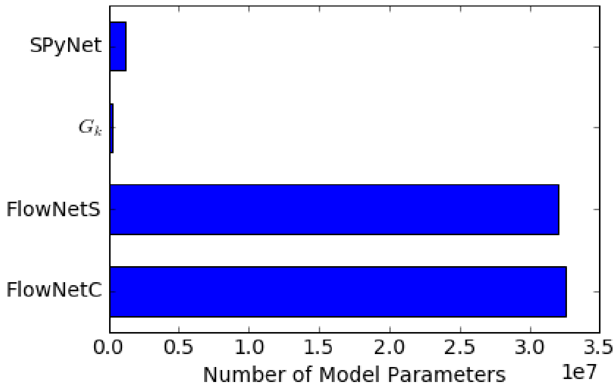

Figure 5. Model size of various methods. Our model is smaller by 96% compared to previous state of the art in end-to-end deep learning.

resembling KITTI would help significantly. We note that SPyNet is significantly more accurate, however, on Middlebury, where FlowNet has trouble with the small motions. Note that both learned methods are still less accurate than Classic+NL on Middlebury but both are also significantly faster.

5. Analysis

We evaluate the performance of our model in terms of its speed and accuracy in comparison to previous optical flow methods. We compare our model size with previous deep networks and interpret the our learned filters.

5.1. Model Size

Combining the spatial pyramid approach to flow estimation with a convnet approach results in a huge reduction in model complexity. At each pyramid level, a network, G_k, has 240,050 parameters that are learned while training. The total number of parameters learned by the entire network is 1,200,250, with 5 spatial pyramid levels. In comparison, FlowNetS and FlowNetC [15] have 32,070,472 and 32,561,032 parameters respectively. Our model is smaller by about 96 % in comparison; this is illustrated in Fig. 5.

The spatial pyramid approach to learning optical flow leads to a significant reduction of model parameters without sacrificing accuracy. There are two reasons that contribute to this reduction - the warping function and learning of residual flow. The warping function is a non-linear function that stretches and squeezes the image according to the flow field. It has been used widely in the optical flow literature [39] to achieve state of the art performance. It might be possible to learn this function with several layers of a convolution network and enough data. By using the warping function directly, we reduce the parameters require to model it in a convnet. More importantly, the residual learning restricts the range of flow fields that need to be learned in the output space. As such, each of our networks only has to model a smaller range of velocities at each level of the spatial pyramid.

Our network as a small memory footprint. The disc space required to store all the model parameters is 9.7 MB. As such, it can be easily deployed to mobile devices and tablets with GPU support. As a feedforward deep network, our models could run in real-time on phones and small devices.

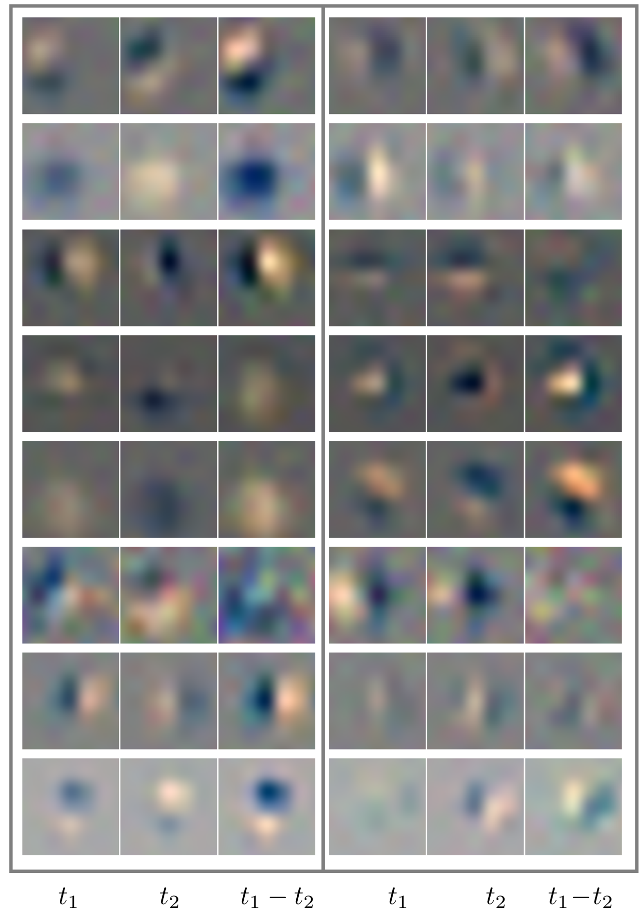

Figure 6. Visualization of filter weights in the first layer of G_2 showing their spatiotemporal nature on RGB image pair.

5.2. Visualization of Learned Filters

To gain insight into the method and to relate it to prior work on optical flow, we explore the filters learned by the network. Figure 6 shows examples of filters learned by the first layer of the network, G_2. In each row, the first two columns show the spatial filters that operate on the RGB channels of the two input images respectively. The third column is the difference between the two spatial filters hence representing the temporal features learned by our model. We observe that most of the spatio-temporal filters in Fig. 6 are equally sensitive to all color channels, and hence appear mostly grayscale. Note that the actual filters are 7×7 pixels and here they are upsampled for visualization.

We observe that many of the spatial filters appear to be similar to traditional Gaussian derivative filters used by classical methods. These classical filters are hand crafted and typically are applied in the horizontal and vertical direction. Here we observe a greater variety of derivative-like filters of varied scales and orientations. We also observe filters that spatially resemble second derivative or Gabor filters [2]. The temporal filters show a clear derivative-like structure in time.

Note that these filters are very different from those reported in [15] (Sup. Mat.), which have a high-frequency structure, unlike classical filters.

Figure 7 illustrates how filters learned by the network at each level of the pyramid differ from each other. Recall that, during training, each network is initialized with the network before it in the pyramid. The filters, however, do not stay exactly the same with training. Most of the filters in our network look like rows 1 and 2, where the filters become sharper as we progress towards the finer-resolution levels of the pyramid. However, there are some filters that are similar to rows 3 and 4, where these filters become more defined at higher resolution levels of the pyramid. There are very few filters that appear to change completely across the pyramid levels as seen in rows 5 and 6.

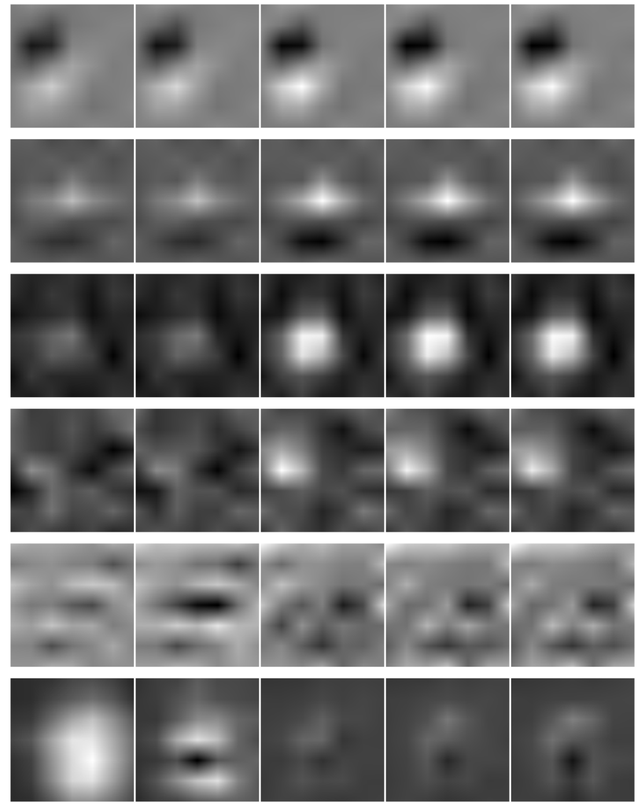

Figure 7. Evolution of filters across the pyramid levels (from low resolution (0) to high resolution (4))

5.3. Speed

Optical flow estimation is traditionally viewed as an optimization problem involving some form of variational inference. As a result, most of the optical flow algorithms are often computationally expensive, taking several seconds or minutes per frame. Arguably this has limited the application of optical flow in robotics, embedded systems, and video analysis.

Using a GPU can improve speed of traditional methods [46, 40] but with reduced accuracy. Feed forward deep networks [15] leverage fast GPU convolutions to speed up computations and look like the most promising methods to balance speed and accuracy. Of course for embedded applications, network size becomes critical (see Fig. 5).

To our knowledge, SPyNet is the fastest optical flow method with an accuracy in the range of popular methods. Figure 8 shows the speed-accuracy comparisons of several well known methods. All times shown are measured with the images already loaded in the memory. The errors are computed as the average EPE of both the clean and final MPI-Sintel sequences.

6. Discussion

A traditional approach for minimizing brightness constancy error linearizes the brightness constancy equation using a first-order Taylor series. Such methods rely on a small set of linear filters: two spatial derivative filters in x and y and a temporal derivative. Sometimes, they add a more generic filter constancy assumption [1, 8]. These methods all rely on iterative optimization to minimize an error function.

Here, the filters are somewhat different. Instead of a small number, we learn a large filter bank and use them differently. There is no explicit iterative optimization. Rather, here the set of filters are used in the direct computation of the flow by the feed-forward network.

We also note that there is a long literature on learning or modeling filters for optical flow [35]. We note that our first level 7x7 filters typically have a larger spatial extent than most filters currently used on optical flow methods.

The network we learn is small compared with other recent optical flow networks. Examination of the filters, however, suggests that it might be possible to make it significantly smaller still. Many of the filters resemble derivative

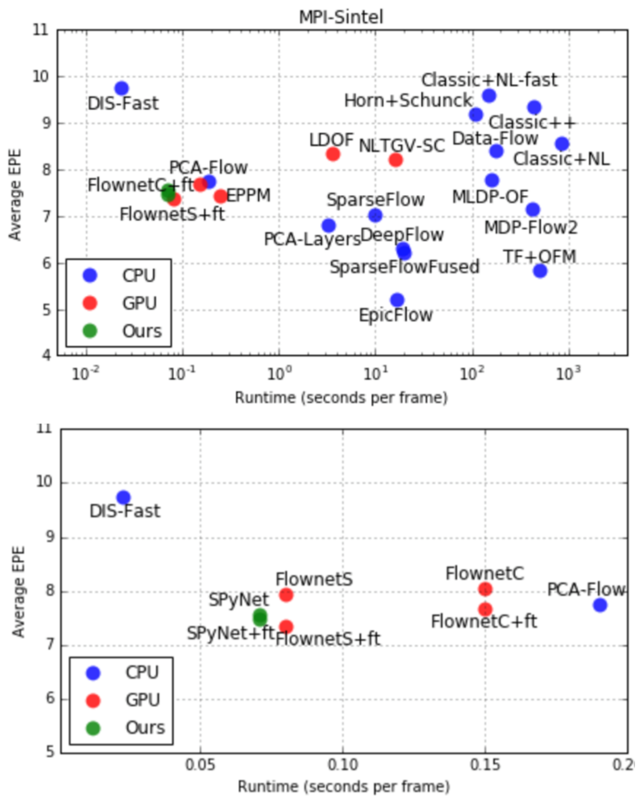

Figure 8. Average EPE vs. runtime on MPI-Sintel. EPE computed as the average of the clean and final passes. Zoomed in version on the bottom shows just the fastest methods. Adapted from [47].

of Gaussian filters or Gabor filters at various scales, orientations, spatial frequencies, and spatial shifts. Given this, it may be possible to significantly compress the filter bank by using dimensionality reduction or by using a set of analytic spatio-temporal features.

Early methods for optical flow used analytic spatio-temporal features but, at the time, did not produce good results and the general line of spatio-temporal filtering decayed. The difference from early work is that our approach suggests the need for a large filter bank of varied filters. Note also that these approaches considered only the first convolutional layer of filters and did not seek a "deep" solution. This all suggests the possibility that a deep network of analytic filters could perform well. This could vastly reduce the size of the network and the number of parameters that need to be learned. In the spatial domain, for example, there is work relating the filters of convnets to wavelets [28].

Note that pyramids have well-known limitations for dealing with large motions [7, 36]. In particular, small or thin objects that move quickly effectively disappear at coarse pyramid levels, making it impossible for the pyramid to capture their motion. Recent approaches for dealing with such large motions use sparse matching to augment standard pyramids [45, 7]. This suggests training a separate network for the task of large motion estimation and combining this with our SPyNet. Alternatively Sevilla et al. [36] define a different kind of image representation that, when used in a pyramid, preserves fine structures; perhaps this could be learned.

7. Future

Future work should extend the method to use more frames (e.g. 3 or 4). This should enable the model to learn richer temporal filters and, for small motions, this might lead to more accurate results. Multiple frames could also enable the network to reason more explicitly about occlusion.

A spatial pyramid can be thought of as the simple application of a set of linear filters. Here we take a standard spatial pyramid but one could learn the filters for the pyramid itself. SPyNet also uses a standard warping function to align images using the flow computed from the previous pyramid level. This too could be learned.

Here we trained the network in a sequential fashion. Better results are likely if the full network can be trained end-to-end. The pyramid down- and up-sampling operations linear functions so they are easy to learn. Image warping, however, is non-linear in the optical flow, complicating the propagation of derivatives through the full pyramid and all the networks.

One appealing feature of SPyNet is that it is small enough to fit on a mobile device. Future work will explore a mobile implementation and its applications.

Finally, Flying Chairs may not be the best dataset for learning our network since it contains many huge displacements that are too large for classical pyramid approaches to capture. Such motions occur in animated films like Sintel but less often in real scenes. We are exploring new training datasets to improve performance on more standard sequences where the motion is less dramatic.

8. Conclusions

In summary, we have described a new optical flow method that combines features of classical optical flow algorithms with deep learning. In a sense, there are two notions of "deepness" here. First we use a "deep" spatial pyramid to deal with large motions. Second we use deep neural networks at each level of the spatial pyramid and train them to estimate a flow *update* at each level. This approach means that each network has less work to do than a fully generic flow method that has to estimate arbitrarily large motions. At each pyramid level we assume that the motion is small (on the order of a pixel). This is borne out by the fact that the network learns spatial and temporal filters that resemble classical derivatives of Gaussians and

Gabors. Because each sub-task is so much simpler, our network needs many fewer parameters than previous methods like FlowNet. This results in a method that is small enough to fit on the phone and that is faster than existing methods. At the same time, SPyNet achieves an accuracy that is comparable to FlowNet or surpasses it in several benchmarks. This opens up the promise of optical flow that is both accurate, practical, and widely deployable.

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References

[1] E. H. Adelson, C. H. Anderson, J. R. Bergen, P. J. Burt, and J. M. Ogden. Pyramid methods in image processing. *RCA engineer*, 29(6):33–41, 1984.

[2] E. H. Adelson and J. R. Bergen. Spatiotemporal energy models for the perception of motion. *J. Opt. Soc. Am. A*, 2(2):284–299, Feb. 1985.

[3] A. Ahmadi and I. Patras. Unsupervised convolutional neural networks for motion estimation. *arXiv preprint arXiv:1601.06087*, 2016.

[4] S. Baker, D. Scharstein, J. Lewis, S. Roth, M. J. Black, and R. Szeliski. A database and evaluation methodology for optical flow. *International Journal of Computer Vision*, 92(1):1–31, 2011.

[5] L. Bao, Q. Yang, and H. Jin. Fast edge-preserving PatchMatch for large displacement optical flow. *Image Processing, IEEE Transactions on*, 23(12):4996–5006, Dec 2014.

[6] J. Barron, D. J. Fleet, and S. S. Beauchemin. Performance of optical flow techniques. *Int. J. Comp. Vis. (IJCV)*, 12(1):43–77, 1994.

[7] T. Brox, C. Bregler, and J. Malik. Large displacement optical flow. In *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*, pages 41–48. IEEE, 2009.

[8] T. Brox, A. Bruhn, N. Papenberg, and J. Weickert. High accuracy optical flow estimation based on a theory for warping. In *European conference on computer vision*, pages 25–36. Springer, 2004.

[9] P. J. Burt and E. H. Adelson. The Laplacian pyramid as a compact image code. *IEEE Transactions on Communications*, COM-34(4):532–540, 1983.

[10] D. J. Butler, J. Wulff, G. B. Stanley, and M. J. Black. A naturalistic open source movie for optical flow evaluation. In A. Fitzgibbon et al. (Eds.), editor, *European Conf. on Computer Vision (ECCV)*, Part IV, LNCS 7577, pages 611–625. Springer-Verlag, Oct. 2012.

[11] C. Cadieu and B. A. Olshausen. Learning transformational invariants from natural movies. In *Advances in neural information processing systems*, pages 209–216, 2008.

[12] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille. Semantic image segmentation with deep convolutional nets and fully connected crfs. *arXiv preprint arXiv:1412.7062*, 2014.

[13] S. D., S. Roth, J. Lewis, and M. Black. Learning optical flow. In *ECCV*, pages 83–97, 2008.

[14] E. L. Denton, S. Chintala, R. Fergus, et al. Deep generative image models using a laplacian pyramid of adversarial networks. In *Advances in neural information processing systems*, pages 1486–1494, 2015.

[15] A. Dosovitskiy, P. Fischery, E. Ilg, C. Hazirbas, V. Golkov, P. van der Smagt, D. Cremers, T. Brox, et al. Flownet: Learning optical flow with convolutional networks. In *2015 IEEE International Conference on Computer Vision (ICCV)*, pages 2758–2766. IEEE, 2015.

[16] W. T. Freeman, E. C. Pasztor, and O. T. Carmichael. Learning low-level vision. *International Journal of Computer Vision*, 40(1):25–47, 2000.

[17] A. Geiger, P. Lenz, and R. Urtasun. Are we ready for autonomous driving? the KITTI vision benchmark suite. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2012.

[18] F. Glazer. *Hierarchical motion detection*. PhD thesis, University of Massachusetts, Amherst, MA, 1987. COINS TR 87–02.

[19] Z. Han, Z. Xu, and S.-C. Zhu. Video primal sketch: A generic middle-level representation of video. In *2011 International Conference on Computer Vision*, pages 1283–1290. IEEE, 2011.

[20] S. Hauberg, A. Feragen, R. Enficiaud, and M. Black. Scalable robust principal component analysis using Grassmann averages. *IEEE Trans. Pattern Analysis and Machine Intelligence (PAMI)*, Dec. 2015.

[21] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. *arXiv preprint arXiv:1512.03385*, 2015.

[22] D. J. Heeger. Model for the extraction of image flow. *J. Opt. Soc. Am*, 4(8):1455–1471, Aug. 1987.

[23] B. K. Horn and B. G. Schunck. Determining optical flow. *1981 Technical Symposium East*, pages 319–331, 1981.

[24] B. K. P. Horn. *Robot Vision*. The MIT Press, Cambridge, Massachusetts, 1986.

[25] D. Kingma and J. Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

[26] T. Kroeger, R. Timofte, D. Dai, and L. V. Gool. Fast optical flow using dense inverse search. In *Computer Vision – ECCV*, 2016.

[27] J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3431–3440, 2015.

[28] S. Mallat. Understanding deep convolutional networks. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, 374(2065), 2016.

[29] M. Mathieu, C. Couprie, and Y. LeCun. Deep multi-scale video prediction beyond mean square error. In *ICLR*, 2016.

[30] R. Memisevic and G. E. Hinton. Learning to represent spatial transformations with factored higher-order boltzmann machines. *Neural Computation*, 22(6):1473–1492, 2010.

[31] B. A. Olshausen. Learning sparse, overcomplete representations of time-varying natural images. In *Image Processing, 2003. ICIP 2003. Proceedings. 2003 International Conference on*, volume 1, pages I–41. IEEE, 2003.

[32] J. Revaud, P. Weinzaepfel, Z. Harchaoui, and C. Schmid. EpicFlow: Edge-Preserving Interpolation of Correspondences for Optical Flow. In *Computer Vision and Pattern Recognition*, 2015.

[33] S. Roth and M. J. Black. Fields of experts. *International Journal of Computer Vision*, 82(2):205–229, 2009.

[34] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015.

[35] H. Scharr. Optimal filters for extended optical flow. In *Complex Motion*, pages 14–29. Springer, 2007.

[36] L. Sevilla-Lara, D. Sun, E. G. Learned-Miller, and M. J. Black. Optical flow estimation with channel constancy. In *Computer Vision – ECCV 2014*, volume 8689 of *Lecture Notes in Computer Science*, pages 423–438. Springer International Publishing, Sept. 2014.

[37] E. P. Simoncelli and D. J. Heeger. A model of neuronal responses in visual area MT. *Vision Res.*, 38(5):743–761, 1998.

[38] D. Sun, S. Roth, and M. J. Black. Secrets of optical flow estimation and their principles. In *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*, pages 2432–2439. IEEE, 2010.

[39] D. Sun, S. Roth, and M. J. Black. A quantitative analysis of current practices in optical flow estimation and the principles behind them. *International Journal of Computer Vision*, 106(2):115–137, 2014.

[40] N. Sundaram, T. Brox, and K. Keutzer. Dense point trajectories by gpu-accelerated large displacement optical flow. In *European conference on computer vision*, pages 438–451. Springer, 2010.

[41] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1–9, 2015.

[42] G. W. Taylor, R. Fergus, Y. LeCun, and C. Bregler. Convolutional learning of spatio-temporal features. In *European conference on computer vision*, pages 140–153. Springer, 2010.

[43] D. Tran, L. Bourdev, R. Fergus, L. Torresani, and M. Paluri. Deep End2End Voxel2Voxel prediction. In *The 3rd Workshop on Deep Learning in Computer Vision*, 2016.

[44] L. van Hateren and J. Ruderman. Independent component analysis of natural image sequences yields spatio-temporal filters similar to simple cells in primary visual cortex. *Proceedings: Biological Sciences*, 265(1412):23152320, 1998.

[45] P. Weinzaepfel, J. Revaud, Z. Harchaoui, and C. Schmid. Deepflow: Large displacement optical flow with deep matching. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 1385–1392, 2013.

[46] M. Werlberger, W. Trobin, T. Pock, A. Wedel, D. Cremers, and H. Bischof. Anisotropic Huber-L1 optical flow. In *BMVC*, London, UK, September 2009.

[47] J. Wulff and M. J. Black. Efficient sparse-to-dense optical flow estimation using a learned basis and layers. In *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 120–130. IEEE, 2015.

[48] J. J. Yu, A. W. Harley, and K. G. Derpanis. Back to basics: Unsupervised learning of optical flow via brightness constancy and motion smoothness. *arXiv preprint arXiv:1608.05842*, 2016.