Boulder

Computer Vision; Image Transformation; Optical Flow and Depth Estimation

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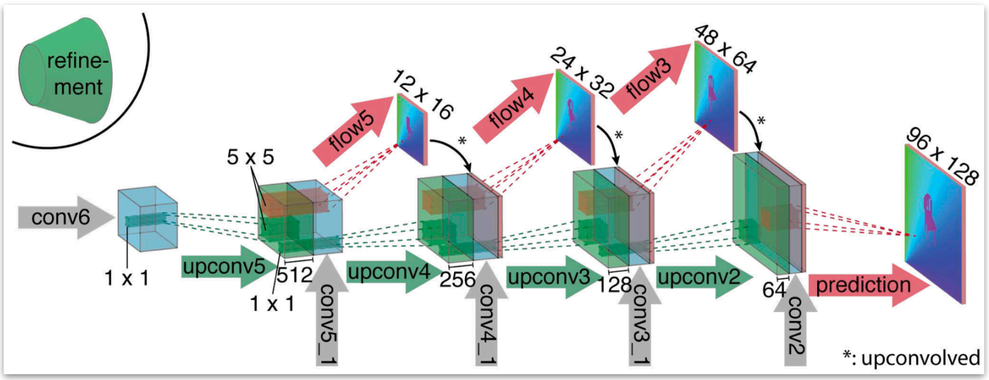
FlowNet: Learning Optical Flow with Convolutional Networks

Given a dataset consisting of image pairs and ground truth flows, train a network to predict the x-y flow fields directly from the images.

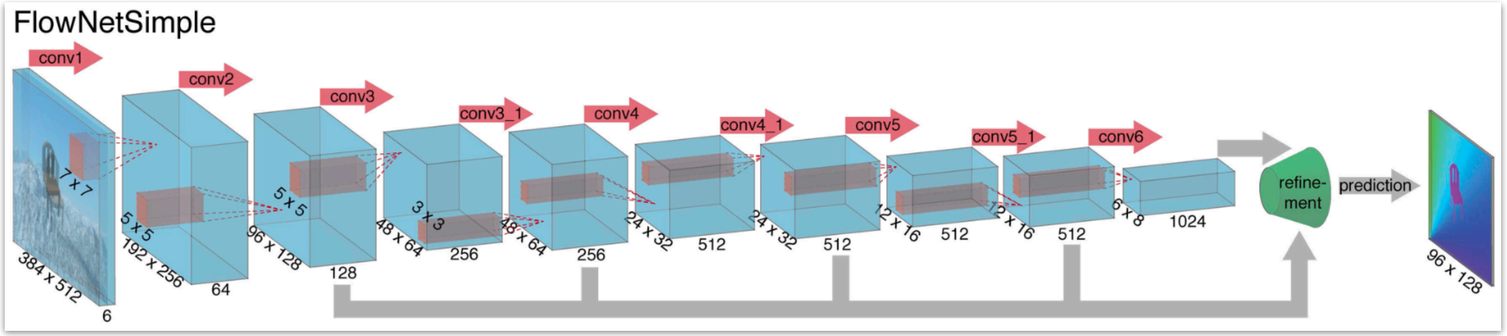
Flying Chairs Dataset

Data Augmentation

upconv: unpooling + conv



FlowNetSimple



	Frame pairs	Frames with ground truth	Ground truth density per frame
Middlebury	72	8	100%
KITTI	194	194	∽50%
Sintel	1,041	1,041	100%
Flying Chairs	22,872	22,872	100%

Method	Sintel Clean		Sintel Final		KITTI		Middlebury train		Middlebury test		Chairs	Time (sec)	
	train	test	train	test	train	test	AEE	AAE	AEE	AAE	test	CPU	GPU
EpicFlow [30]	2.27	4.12	3.57	6.29	3.47	3.8	0.31	3.24	0.39	3.55	2.94	16	-
DeepFlow [35]	3.19	5.38	4.40	7.21	4.58	5.8	0.21	3.04	0.42	4.22	3.53	17	-
EPPM [3]	-	6.49	-	8.38	-	9.2	-	-	0.33	3.36	-	-	0.2
LDOF [6]	4.19	7.56	6.28	9.12	13.73	12.4	0.45	4.97	0.56	4.55	3.47	65	2.5
FlowNetS	4.50	7.42	5.45	8.43	8.26	-	1.09	13.28	-	-	2.71	-	0.08
FlowNetS+v	3.66	6.45	4.76	7.67	6.50	-	0.33	3.87	-	-	2.86	-	1.05
FlowNetS+ft	(3.66)	6.96	(4.44)	7.76	7.52	9.1	0.98	15.20	-	-	3.04	-	0.08
FlowNetS+ft+v	(2.97)	6.16	(4.07)	7.22	6.07	7.6	0.32	3.84	0.47	4.58	3.03	-	1.05

Images | Ground truth | FlowNetS

End Point Error (EPE) Loss: Euclidean distance between the predicted flow vector and the ground truth, averaged over all pixels

Dosovitskiy, Alexey, et al. "Flownet: Learning optical flow with convolutional networks." *Proceedings of the IEEE international conference on computer vision*. 2015.

FlowNet 2.0: Evolution of Optical Flow Estimation with Deep Networks

– problems with small displacements

– noisy artifacts in estimated flow fields

Dataset Schedules

Numbers indicate endpoint errors on Sintel train clean

Architecture	Datasets	S_{short}	S_{long}	S_{fine}
FlowNetS	Chairs	4.45	-	-
	Chairs	-	4.24	4.21
	Things3D	-	5.07	4.50
	mixed	-	4.52	4.10
	Chairs→Things3D	-	4.24	**3.79**
FlowNetC	Chairs	3.77	-	-
	Chairs→Things3D	-	3.58	**3.04**

Training on Chairs first and fine-tuning on Things3D yields the best results. FlowNetC performs better than FlowNetS.

Stacking Networks

$I_1, I_2 \rightarrow$ images $\quad w = (u, v)^T \rightarrow$ previous flow estimation

$\widetilde{I}_2(x, y) = I_2(x + u, y + v) \rightarrow$ warp the second image I_2 (bilinear interpolation)

$e = \|\widetilde{I}_2(x, y) - I_1\| \rightarrow$ error ($\widetilde{I}_2$ should be close to I_1)

FlowNetCorr

$f_1, f_2 \in \mathbb{R}^{w \times h \times c}$ or $f_1, f_2 : \mathbb{R}^2 \rightarrow \mathbb{R}^c$

$c(x_1, x_2) \rightarrow$ correlation of two patches centered at x_1 in the first map and x_2 in the second map

$c(x_1, x_2) = \sum_{o \in [-k,k] \times [-k,k]} \langle f_1(x_1 + o), f_2(x_2 + o) \rangle \rightarrow$ for a square patch of size $K = 2k + 1$

$w^2 h^2 c K^2 \rightarrow$ computational cost

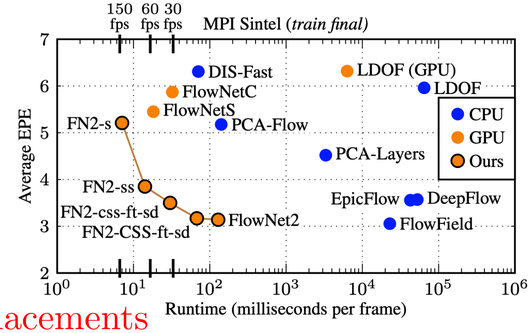
compute $c(x_1, x_2)$ only in a neighborhood of x_1 of size $D = 2d + 1$

$whD^2 cK^2 \rightarrow$ computational cost

$w \times h \times D^2 \rightarrow$ output size

use stride s_1 to quantize x_1 globally

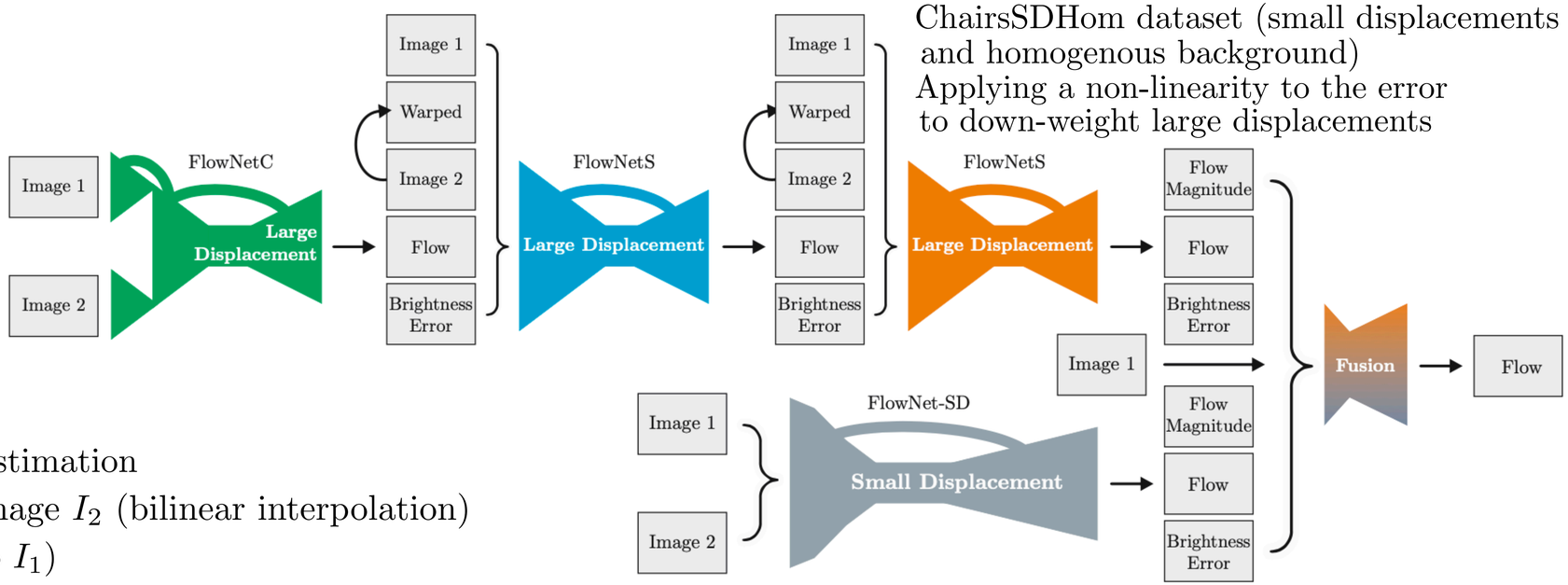
use stride s_2 to quantize x_2 locally around x_1



Small Displacements

ChairsSDHom dataset (small displacements and homogenous background)

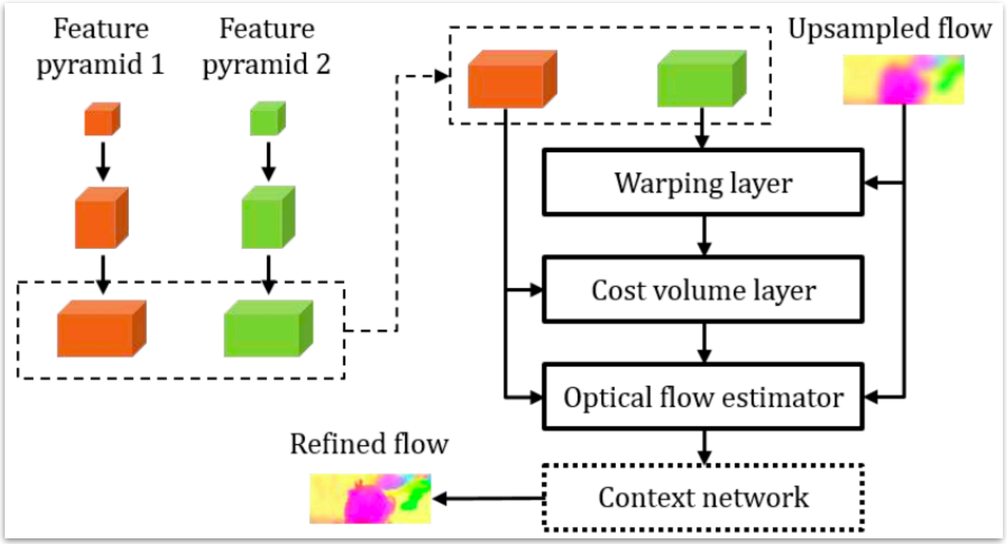
Applying a non-linearity to the error to down-weight large displacements



Ilg, Eddy, et al. "Flownet 2.0: Evolution of optical flow estimation with deep networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.

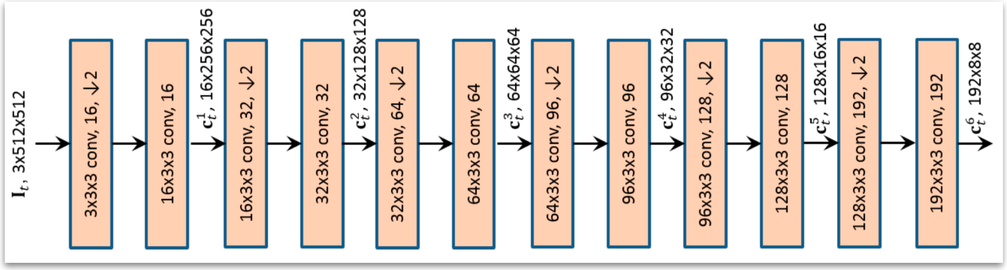
PWC-Net: CNNs for Optical Flow Using Pyramid, Warping, and Cost Volume

– action recognition – autonomous driving – video editing
– FlyingChairs dataset (training)
– FlyingThings3D dataset (fine-tuning)
– Sintel (fine-tuning)
– KITTI (fine-tuning)
Combining deep learning with domain knowledge!



Feature Pyramid Extractor

$t = 1, 2 \rightarrow$ first, second image

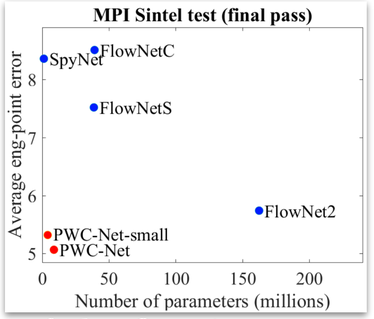


Warping Layer

Warp features of the second image toward the first image using the $\times 2$ upsampled flow from the $(l+1)$-th level

$$\mathbf{c}_w^l(\mathbf{x}) = \mathbf{c}_2^l\left(\mathbf{x} + \text{up}_2(\mathbf{w}^{l+1})(\mathbf{x})\right) \rightarrow \text{bi-linear interpolation}$$

($\mathbf{x}$: pixel index; $\mathbf{w}^{l+1}$: flow)



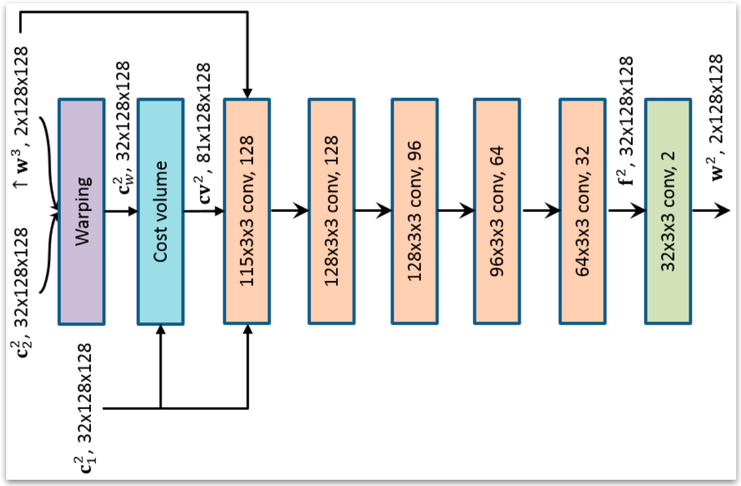
Cost Volume Layer

$$\mathbf{cv}^l(\mathbf{x}_1, \mathbf{x}_2) = \frac{1}{N}\left(\mathbf{c}_1^l(\mathbf{x}_1)\right)^\top \mathbf{c}_w^l(\mathbf{x}_2) \rightarrow \text{correlation between features of the first image and warped features of the second image}$$

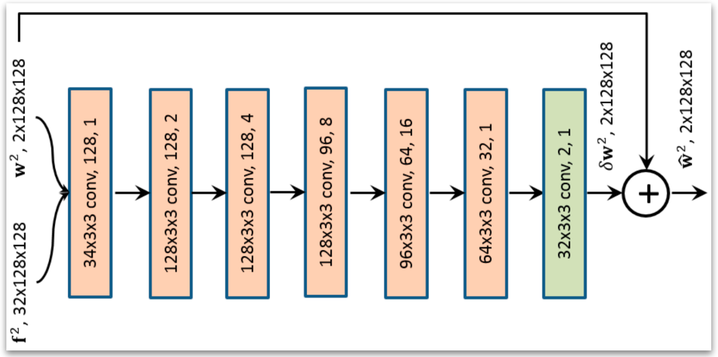
$|\mathbf{x}_1 - \mathbf{x}_2|_\infty \leq d \rightarrow$ limited range of d pixels

$d^2 \times H^l \times W^l \rightarrow$ dimension of the 3D cost volume

Optical Flow Estimator



Context Network



Training Loss

$$\mathcal{L}(\Theta) = \sum_{l=l_0}^{L} \alpha_l \sum_{\mathbf{x}} |\mathbf{w}_\Theta^l(\mathbf{x}) - \mathbf{w}_{\text{GT}}^l(\mathbf{x})|_2 + \gamma|\Theta|_2$$

$$\mathcal{L}(\Theta) = \sum_{l=l_0}^{L} \alpha_l \sum_{\mathbf{x}} \left(|\mathbf{w}_\Theta^l(\mathbf{x}) - \mathbf{w}_{\text{GT}}^l(\mathbf{x})| + \epsilon\right)^q + \gamma|\Theta|_2$$

Fine-tuning Loss

Sun, Deqing, et al. "Pwc-net: Cnns for optical flow using pyramid, warping, and cost volume." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.

Unsupervised Monocular Depth Estimation with Left-Right Consistency

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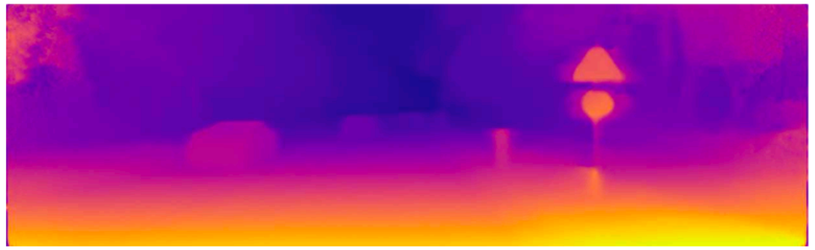


$I \rightarrow$ a single image at test time

$z = g(I) \rightarrow$ per-pixel depth prediction

$g \rightarrow$ to be learned

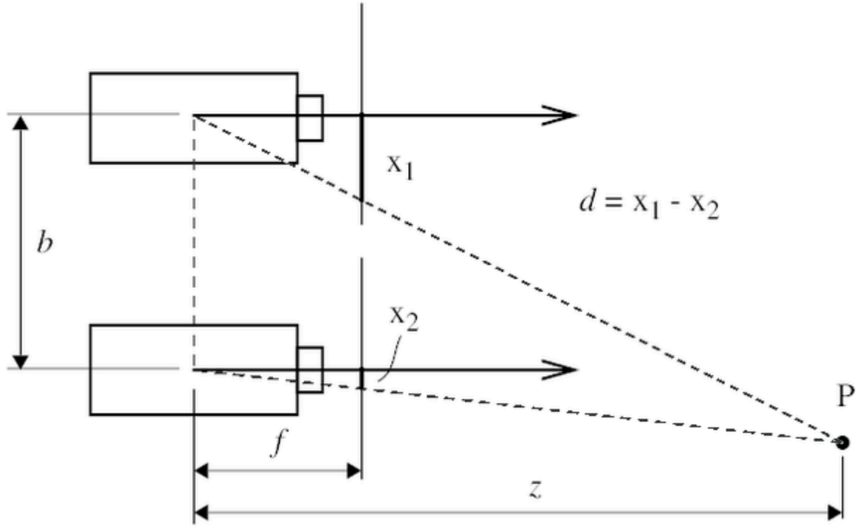
It is presently not practical to treat this as a supervised learning problem; Laser scanners are expensive and can be imprecise in natural scenes featuring movement and reflections.

Depth Estimation as Image Reconstruction

The intuition here is that, given a calibrated pair of binocular cameras, if we can learn a function that is able to reconstruct one image from the other, then we have learned something about the 3D shape of the scene that is being imaged.

Training data (KITTI)

$I^l, I^r \rightarrow$ left and right rectified stereo image pairs



$f \rightarrow$ camera focal length

$b \rightarrow$ baseline distance between the cameras

$z \rightarrow$ depth $\qquad \frac{d}{b} = \frac{f}{z} \rightarrow$ similar triangles

$d \rightarrow$ disparity

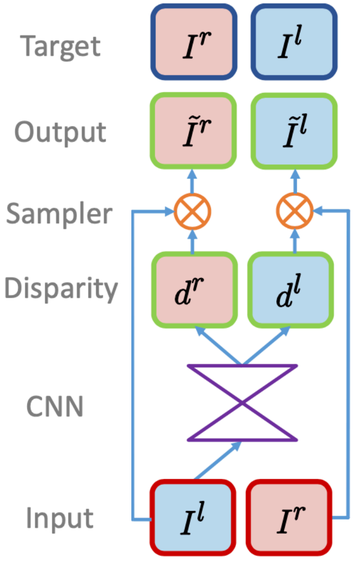
$z = \frac{bf}{d} \rightarrow$ recover depth from disparity

Training Loss

$C = \sum_{s=1}^{4} C_s \rightarrow$ total loss

$C_s \rightarrow$ loss at scale s

$$C_s = \alpha_{ap}(C_{ap}^l + C_{ap}^r) + \alpha_{ds}(C_{ds}^l + C_{ds}^r) + \alpha_{lr}(C_{lr}^l + C_{lr}^r)$$



Bilinear sampling (differentiable)

Test Time

Use d^l and discard d^r

Applications: synthetic object insertion in computer graphics, synthetic depth of field in computational photography, grasping in robotics, using depth as a cue in human body pose estimation, robot assisted surgery, automatic 2D to 3D conversion in film, and self-driving cars.

Appearance Matching

$$C_{ap}^l = \frac{1}{N}\sum_{i,j} \alpha \frac{1 - \text{SSIM}(I_{ij}^l, \tilde{I}_{ij}^l)}{2} + (1-\alpha)\left\| I_{ij}^l - \tilde{I}_{ij}^l \right\|$$

SSIM $\rightarrow$ Structural Similarity

https://en.wikipedia.org/wiki/Structural_similarity#Algorithm

Disparity Smoothness

$$C_{ds}^l = \frac{1}{N}\sum_{i,j} \left|\partial_x d_{ij}^l\right| e^{-\left\|\partial_x I_{ij}^l\right\|} + \left|\partial_y d_{ij}^l\right| e^{-\left\|\partial_y I_{ij}^l\right\|}$$

edge-aware weights: depth discontinuities often occur at image gradients

Left-Right Disparity Consistency

$$C_{lr}^l = \frac{1}{N}\sum_{i,j} \left| d_{ij}^l - d_{ij+d_{ij}^l}^r \right|$$

Godard, Clément, Oisin Mac Aodha, and Gabriel J. Brostow. "Unsupervised monocular depth estimation with left-right consistency." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.

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Questions?