Boulder

Computer Vision; Image Transformation; Optical Flow and Depth Estimation

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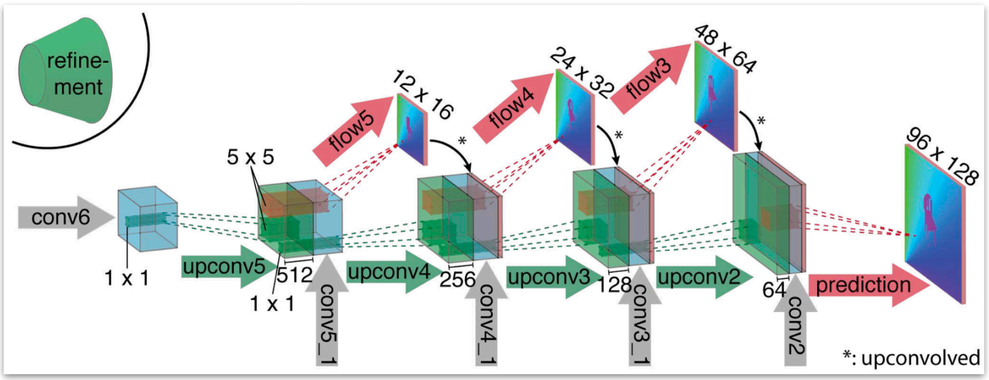
FlowNet: Learning Optical Flow with Convolutional Networks

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.

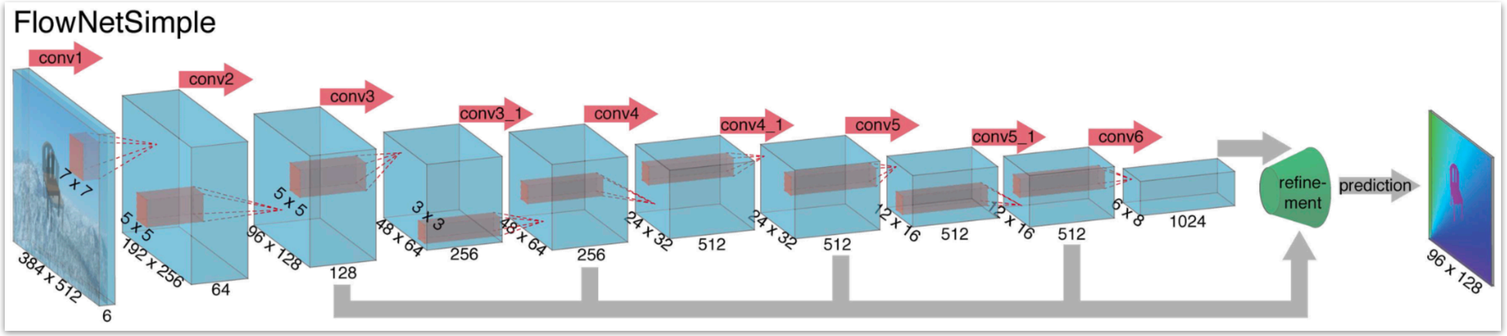
Flying Chairs Dataset

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

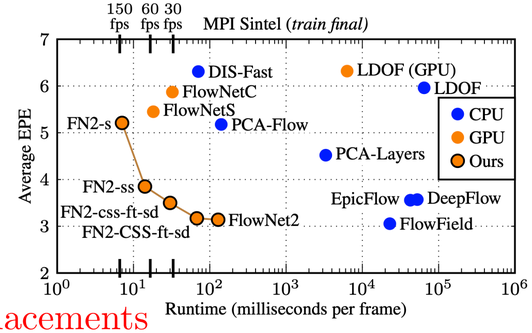
compute $c(x_1, x_2)$ only in a neighborhood of x_1 of size $D = 2d + 1$

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

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

use stride s_1 to quantize x_1 globally

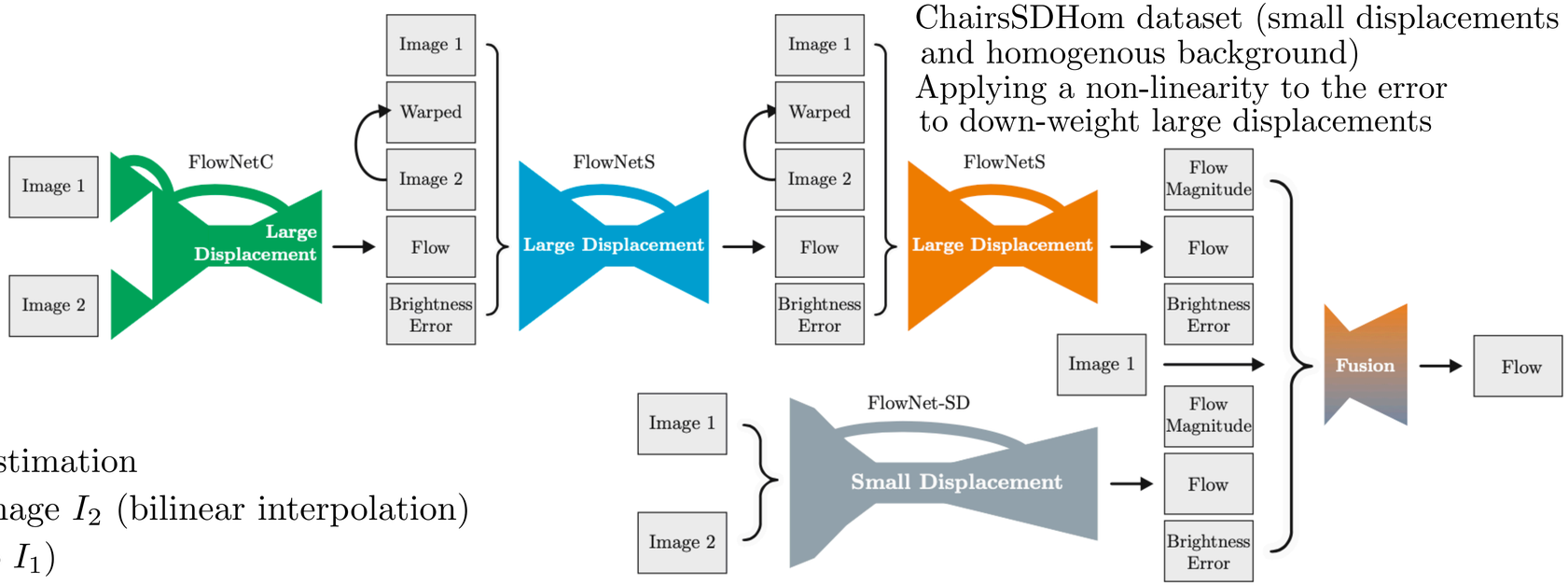
use stride s_2 to quantize x_2 locally around x_1



Small Displacements

ChairsSDHom dataset (small displacements and homogenous background)

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

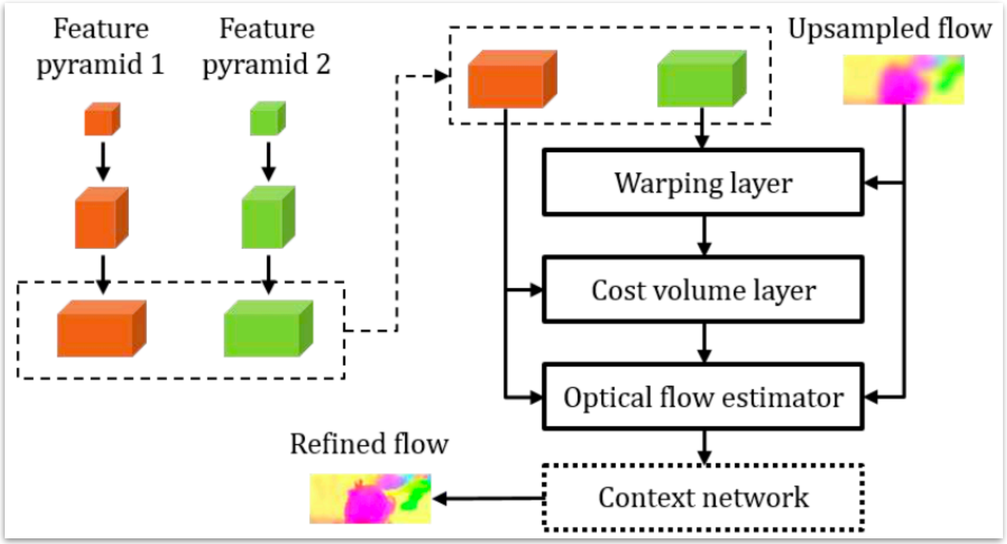


Ilg, Eddy, et al. "Flownet 2.0: Evolution of optical flow estimation with deep networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.

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

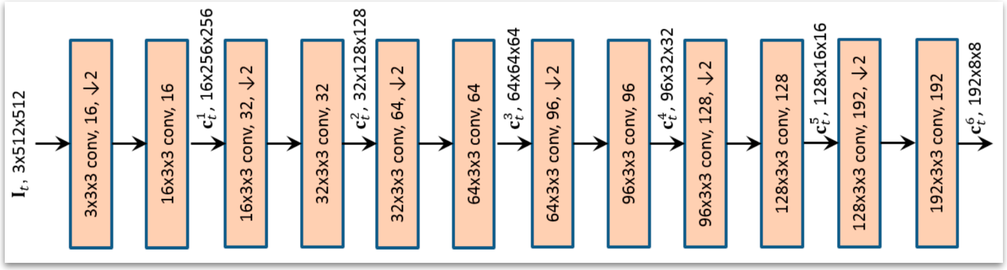
– action recognition – autonomous driving – video editing
– FlyingChairs dataset (training)
– FlyingThings3D dataset (fine-tuning)
– Sintel (fine-tuning)
– KITTI (fine-tuning)

Combining deep learning with domain knowledge!



Feature Pyramid Extractor

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

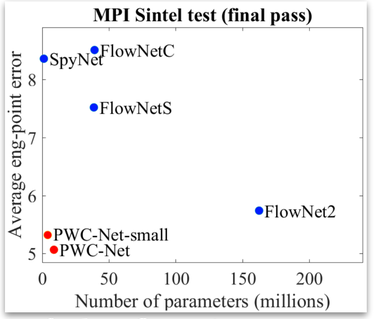


Warping Layer

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)



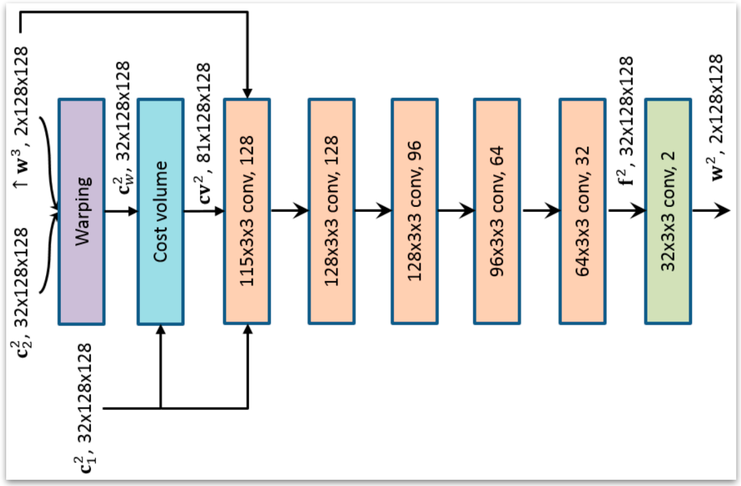
Cost Volume Layer

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

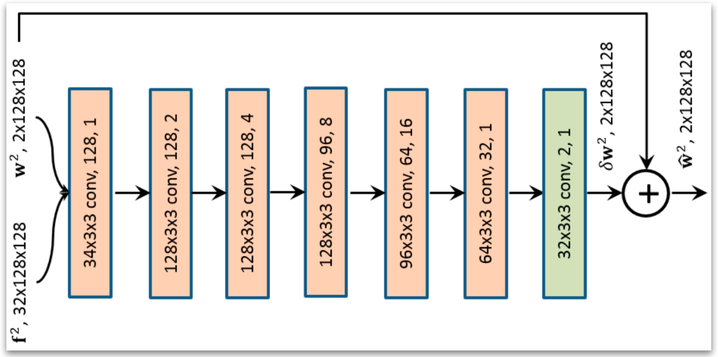
$|\mathbf{x}_1 - \mathbf{x}_2|_\infty \leq d \rightarrow$ limited range of d pixels

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

Optical Flow Estimator



Context Network



Training Loss

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

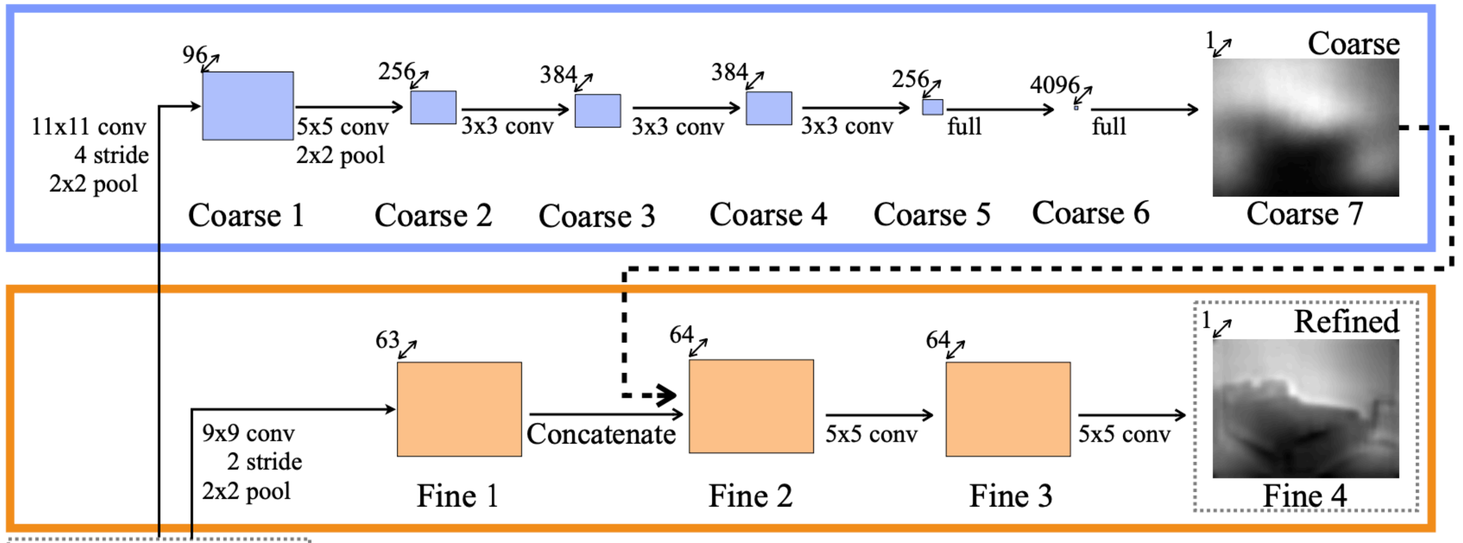
$$\mathcal{L}(\Theta) = \sum_{l=l_0}^{L} \alpha_l \sum_{\mathbf{x}} \left(|\mathbf{w}_\Theta^l(\mathbf{x}) - \mathbf{w}_{\text{GT}}^l(\mathbf{x})| + \epsilon\right)^q + \gamma|\Theta|_2$$

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.

Depth Map Prediction from a Single Image using a Multi-Scale Deep Network

3D geometry of a scene!
– NYU Depth Dataset (Microsoft Kinect Camera)
– KITTI Dataset (Depth Sensors)



		Coarse					Fine
Layer	input	1	2,3,4	5	6	7	1,2,3,4
Size (NYUDepth)	304x228	37x27	18x13	8x6	1x1	74x55	74x55
Size (KITTI)	576x172	71x20	35x9	17x4	1x1	142x27	142x27
Ratio to input	/1	/8	/16	/32	–	/4	/4

Global Coarse-Scale Network

Pre-trained on ImageNet
Global understanding of the full scene

Local Fine-Scale Network

Train the coarse network first, then train the fine network

Scale-Invariant Error

The global scale of a scene is a fundamental ambiguity in depth prediction.

$y \rightarrow$ predicted depth map
$y^* \rightarrow$ ground-truth depth map
$n \rightarrow$ number of pixels indexed with i

$$D(y, y^*) = \frac{1}{n}\sum_{i=1}^{n}(\log y_i - \log y_i^* + \alpha(y, y^*))^2$$

$D(y, y^*)$: scale-invariant mean squared error (in log space)

$$\alpha(y, y^*) = \frac{1}{n}\sum_i(\log y_i^* - \log y_i)$$

α: the value of α that minimizes the error for a given (y, y^*)

All scalar multiples of y have the same error!

Training Loss

$$L(y, y^*) = \frac{1}{n}\sum_i d_i^2 - \frac{\lambda}{n^2}\left(\sum_i d_i\right)^2$$

$$d_i = \log y_i - \log y_i^*$$

If $\lambda = 1$ then $L(y, y^*) = D(y, y^*)$.

Evaluation Metrics

Threshold: % of y_i s.t. $\max(\frac{y_i}{y_i^*}, \frac{y_i^*}{y_i}) = \delta < thr$

Abs Relative difference: $\frac{1}{|T|}\sum_{y \in T}|y - y^*|/y^*$

Squared Relative difference: $\frac{1}{|T|}\sum_{y \in T}||y - y^*||^2/y^*$

RMSE (linear): $\sqrt{\frac{1}{|T|}\sum_{y \in T}||y_i - y_i^*||^2}$

RMSE (log): $\sqrt{\frac{1}{|T|}\sum_{y \in T}||\log y_i - \log y_i^*||^2}$

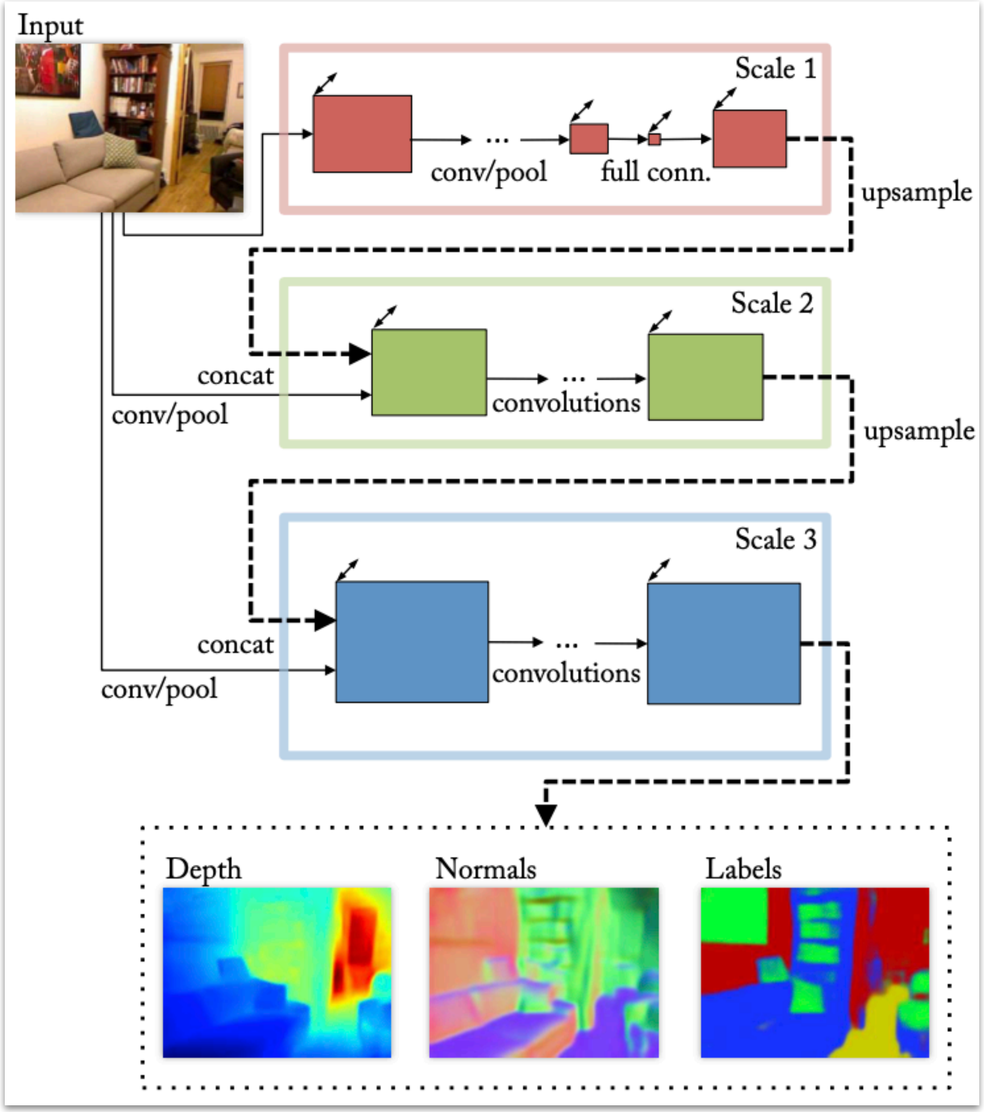
RMSE (log, scale-invariant): The error Eqn. 1

Data Augmentation

- *Scale*: Input and target images are scaled by $s \in [1, 1.5]$, and the depths are divided by s.
- *Rotation*: Input and target are rotated by $r \in [-5, 5]$ degrees.
- *Translation*: Input and target are randomly cropped to the sizes indicated in Fig. 1.
- *Color*: Input values are multiplied globally by a random RGB value $c \in [0.8, 1.2]^3$.
- *Flips*: Input and target are horizontally flipped with 0.5 probability.

Eigen, David, Christian Puhrsch, and Rob Fergus. "Depth map prediction from a single image using a multi-scale deep network." *arXiv preprint arXiv:1406.2283* (2014).

Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture



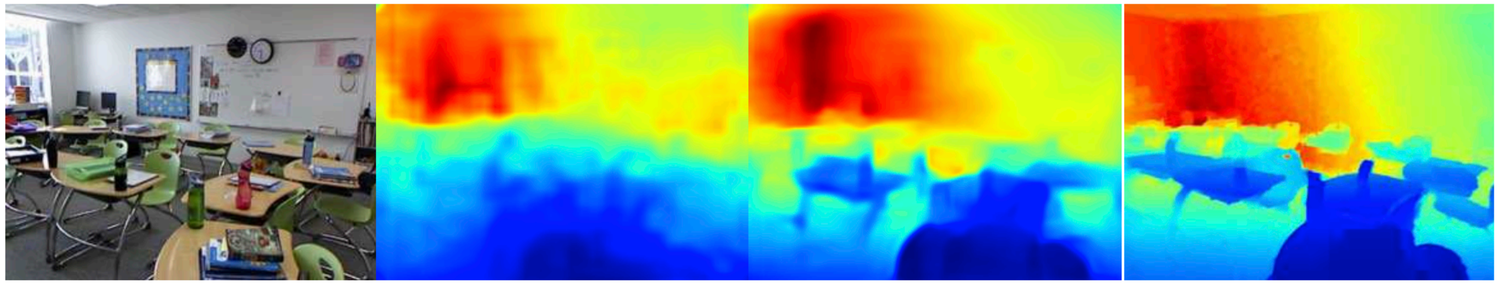
Depth

D & D^* → predicted & ground-truth log depth maps

$d = D - D^*$

$$L_{depth}(D, D^*) = \frac{1}{n}\sum_i d_i^2 - \frac{1}{2n^2}\left(\sum_i d_i\right)^2 + \frac{1}{n}\sum_i [(\nabla_x d_i)^2 + (\nabla_y d_i)^2]$$

Encourage predictions to have not only close-by values, but also similar local structure



Surface Normals

Predict the x, y and z components of the normal at each pixel

$$L_{normals}(N, N^*) = -\frac{1}{n}\sum_i N_i \cdot N_i^* = -\frac{1}{n} N \cdot N^*$$

For ground truth targets, estimate normals from depth by fitting least-squares planes to neighboring sets of points in the point cloud.

Semantic Labels

$$L_{semantic}(C, C^*) = -\frac{1}{n}\sum_i C_i^* \log(C_i)$$

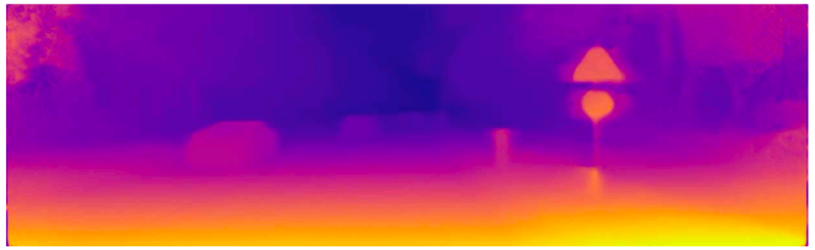
$$C_i = e^{z_i} / \sum_c e^{z_{i,c}}$$

└ softmax

Eigen, David, and Rob Fergus. "Predicting depth, surface normals and semantic labels with a common multi-scale convolutional architecture." *Proceedings of the IEEE international conference on computer vision*. 2015.

Unsupervised Monocular Depth Estimation with Left-Right Consistency

Boulder



$I \rightarrow$ a single image at test time

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

$g \rightarrow$ to be learned

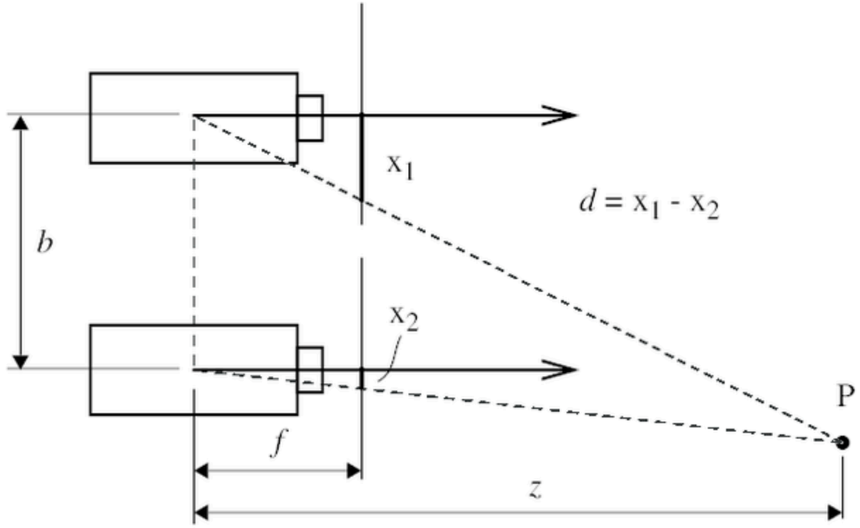
It is presently not practical to treat this as a supervised learning problem; Laser scanners are expensive and can be imprecise in natural scenes featuring movement and reflections.

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

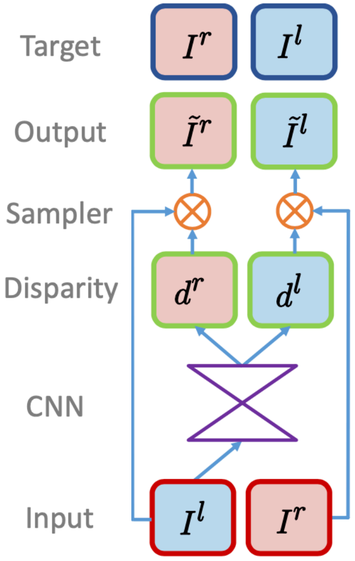
$z = \frac{bf}{d} \rightarrow$ recover depth from disparity

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

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

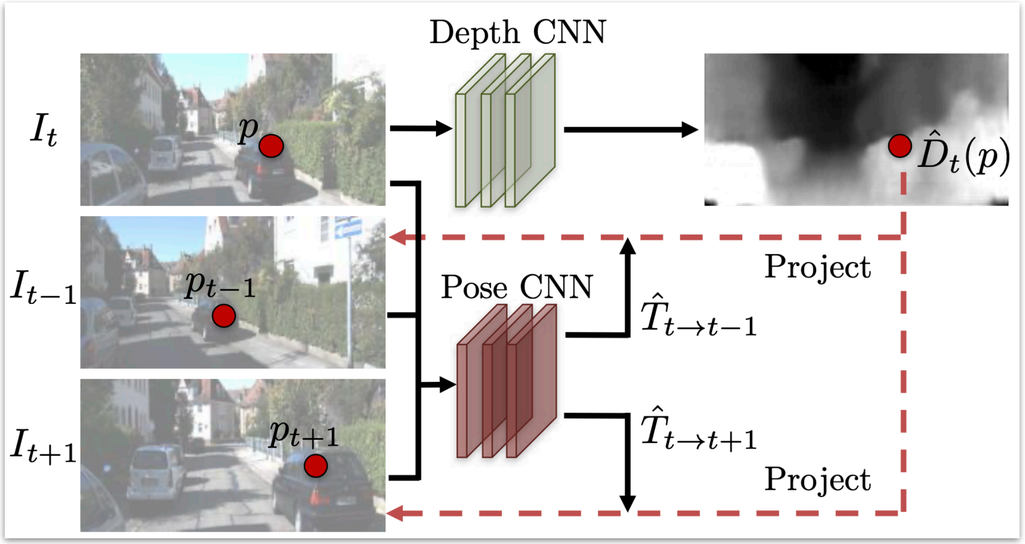
edge-aware weights: depth discontinuities often occur at image gradients

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.

Unsupervised Learning of Depth and Ego-Motion from Video



View synthesis as supervision

$\langle I_1, \ldots, I_N \rangle \rightarrow$ a training mage sequence

$I_t \rightarrow$ target view $(t = 1, \ldots, N)$

$I_s \rightarrow$ source view $(s = 1, \ldots, N, s \neq t)$

$N = 3$

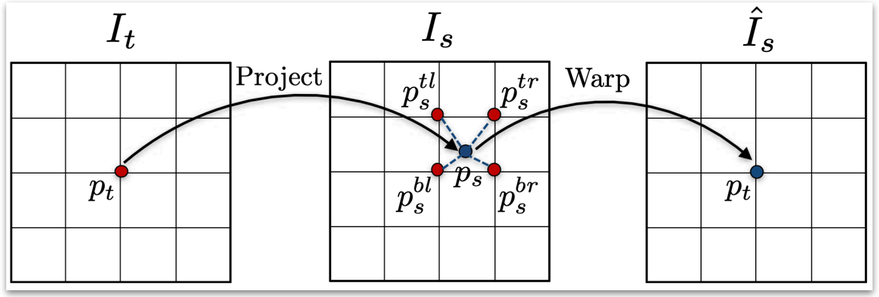
$$\mathcal{L}_{vs} = \sum_s \sum_p |I_t(p) - \hat{I}_s(p)| \rightarrow \text{view synthesis objective}$$

$p \rightarrow$ indexes over pixel coordinates

$\hat{I}_s \rightarrow$ source view I_s warped to the target coordinate frame based on a depth image-based rendering module

Differentiable depth image-based rendering

$p_s \sim K \hat{T}_{t\to s} \hat{D}_t(p_t) K^{-1} p_t \rightarrow p_t$'s projected coordinates onto the source view p_s



$p_t \rightarrow$ homogeneous coordinates of a pixel in the target view

$K \rightarrow$ camera intrinsics matrix

$\hat{D}_t \rightarrow$ predicted depth

$\hat{T}_{t\to s} \rightarrow$ predicted camera pose (transformation matrix)

differentiable bilinear sampling mechanism

Modeling the model limitation

Implicit assumptions:

1) the scene is static without moving objects
2) there is no occlusion/disocclusion between the target view and the source views
3) the surface is Lambertian so that the photo-consistency error is meaningful.

$$\mathcal{L}_{vs} = \sum_{<I_1,\ldots,I_N>\in\mathcal{S}} \sum_p \hat{E}_s(p) |I_t(p) - \hat{I}_s(p)|$$

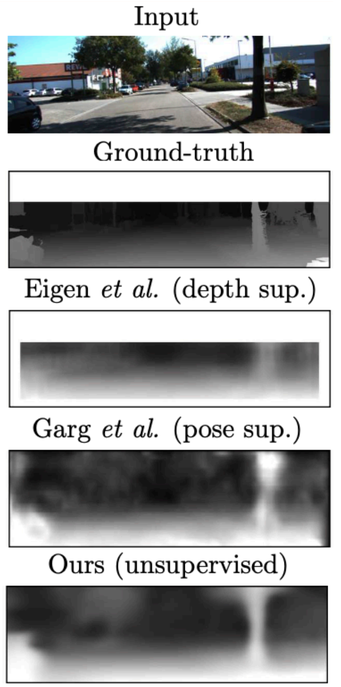
$\hat{E}_s \rightarrow$ explainability prediction network: pre-pixel softmax for each target-source pair

$$\mathcal{L}_{final} = \sum_l \mathcal{L}^l_{vs} + \lambda_s \mathcal{L}^l_{smooth} + \lambda_e \sum_s \mathcal{L}_{reg}(\hat{E}^l_s)$$

l indexes over different image scales

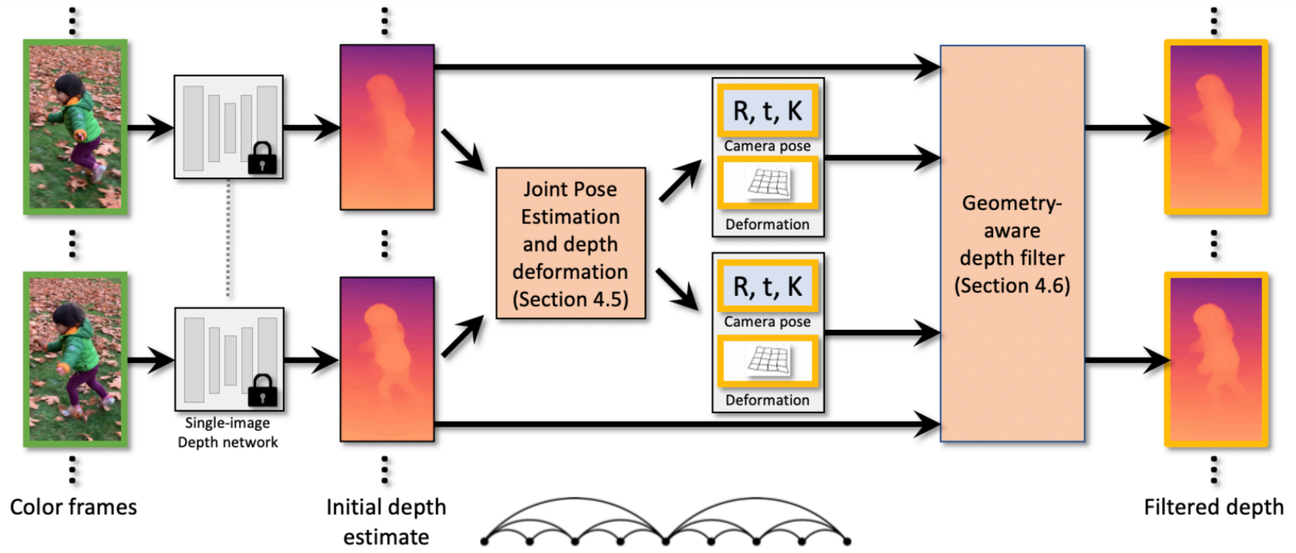
$\mathcal{L}_{reg}$: encourages nonzero predictions by minimizing the cross-entropy loss with constant label 1 at each pixel location

L_1 norm of the second-order gradients for the predicted depth maps



Zhou, Tinghui, et al. "Unsupervised learning of depth and ego-motion from video." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.

Robust Consistent Video Depth Estimation



$P = \{(i,j) : |i-j| = k, i \bmod k = 0, k = 1, 2, 4, \ldots\}$ → set of frame pairs

$f_{i\to j}$ → dense optical flow field
mapping a pixel in frame i to its corresponding location in frame j

$m^{\text{flow}}_{i\to j}$ → binary mask (forward-backward consistent flow pixels)

m^{dyn}_i → binary segmentation mask (Mask R-CNN)
indicating likely dynamic pixels ("person", "animal", "vehicle")

Depth Estimation

p → 2D pixel coordinate

$c_i(p) = s_i d_i(p)\tilde{p}$ → 3D coordinate in frame's i's 3D camera coordinate system

s_i → per-frame scale coefficient

d_i → CNN-estimated depth map

$\tilde{p} = [p_x, p_y, 1]^T$ → homogenous-augmented pixel coordinate

$c_{i\to j}(p) = K_j R_j^T (R_i K_i^{-1} c_i(p) + t_i - t_j)$ → projection of $c_i(p)$ into the camera coordinate system of another frame j

R_i, R_j → rotation of frames i and j

t_i, t_j → translation of frames i and j

K_i, K_j → intrinsics of frames i and j

$$\arg\min_{\theta^{\text{depth}}} \sum_{(i,j)\in P} \sum_{p\in m^{\text{flow}}_{i\to j}} \mathcal{L}^{\text{repro}}_{i\to j}(p), \quad \text{s.t. fixed } \theta^{\text{cam}}$$

$\mathcal{L}^{\text{repro}}_{i\to j}(p) = \mathcal{L}^{\text{sim}}_j(c_{i\to j}(p), c_j(f_{i\to j}(p)))$ → reprojection loss

$\theta^{\text{cam}} = \{R_i, t_i, K_i, s_i\}$ → camara parameters

θ^{depth} → depth CNN parameters

Joint Pose Estimation and Depth Deformation

Reverse the roles of θ^{depth} and θ^{cam}!

Replace s_i with $\phi_i(p) = \sum_k b_k(p) s_i^k$.

$\phi_i(p)$ → depth deformation model

s_i^k → scale factors (defined on a regular grid across the image)

$b_k(p)$ → bilinear coefficients

Geometry-aware Depth Filter

$$d_i^{\text{final}}(p) = \sum_{q\in N(p)} \sum_{j=i-\tau}^{i+\tau} z_{j\to i}(\tilde{f}_{i\to j}(q)) w_{i\to j}(q)$$

$z_{j\to i}$ → reprojected depth (scalar z-component of $c_{j\to i}$)

$\tilde{f}$ → flow field between far frames
(chaining flow maps between consecutive frames)

$w_{i\to j}(q) = \exp(-\lambda_f \mathcal{L}^{\text{ratio}}(c_i(p), c_{j\to i}(\tilde{f}_{i\to j}(q))))$

– Sintel –DAVIS – Cellphone Vides Datasets

$$\mathcal{L}^{sim}(a,b) = \mathcal{L}^{spatial}(a,b) + \mathcal{L}^{ratio}(a,b)$$

$$\mathcal{L}^{spatial}(a,b) = \left\| \frac{a_{xy}}{a_z} - \frac{b_{xy}}{b_z} \right\|_2^2$$

$$\mathcal{L}^{ratio}(a,b) = \frac{\max(a_z, b_z)}{\min(a_z, b_z)} - 1$$

Kopf, Johannes, et al. "Robust Consistent Video Depth Estimation." *ArXiv:2012.05901 [Cs]*, Dec. 2020. *arXiv.org*, http://arxiv.org/abs/2012.05901.

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Questions?