CS231A

Computer Vision: From 3D Reconstruction to Recognition

Optical and Scene Flow

What will you learn today?

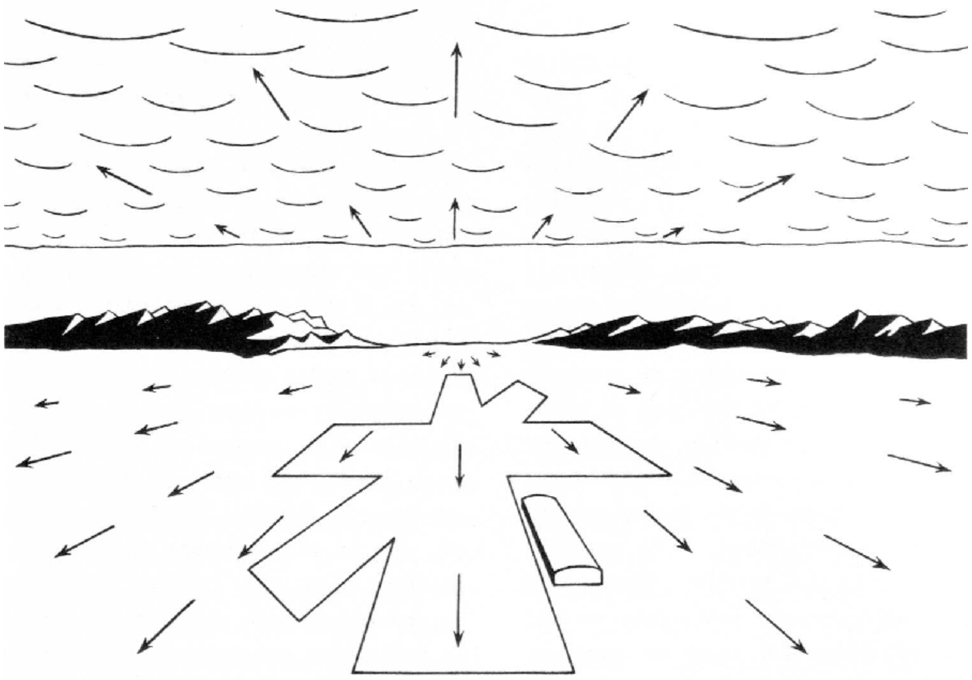
Optical Flow

- What is it and why do you care?
- Assumptions
- Formulating the optimization problem
- Solving it

Scene Flow

Learning-based Approaches to Estimating Motion

Optical Flow - What is it?



J. J. Gibson, The Ecological Approach to Visual Perception

Optical Flow - What is it?

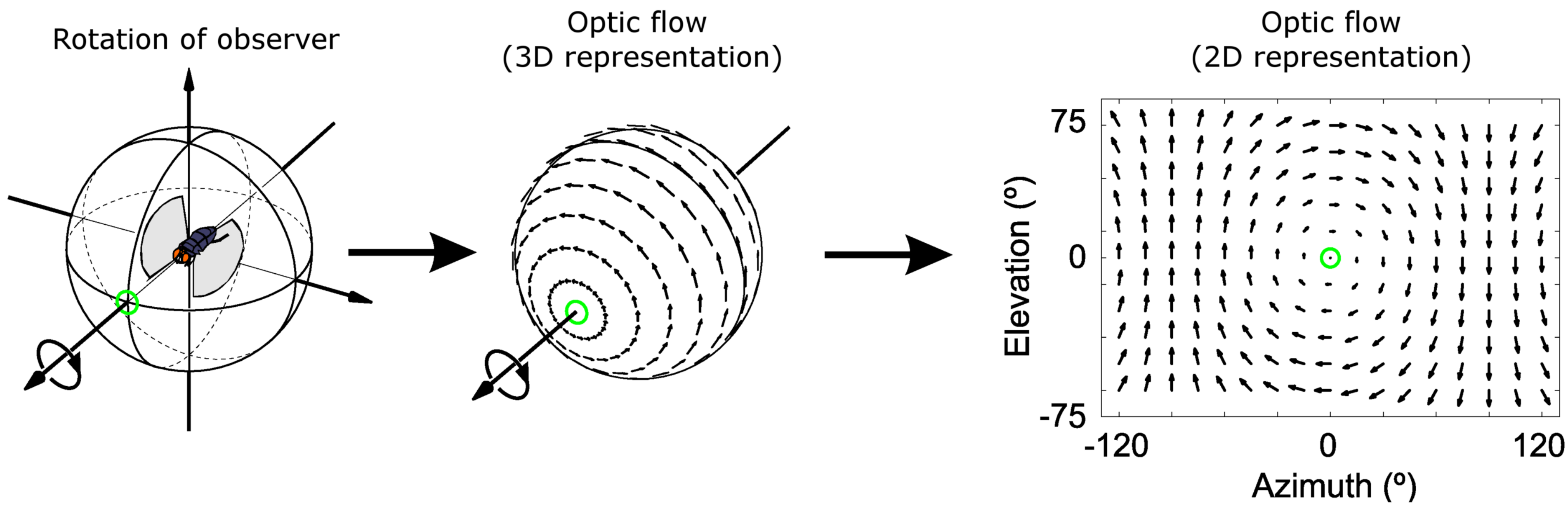
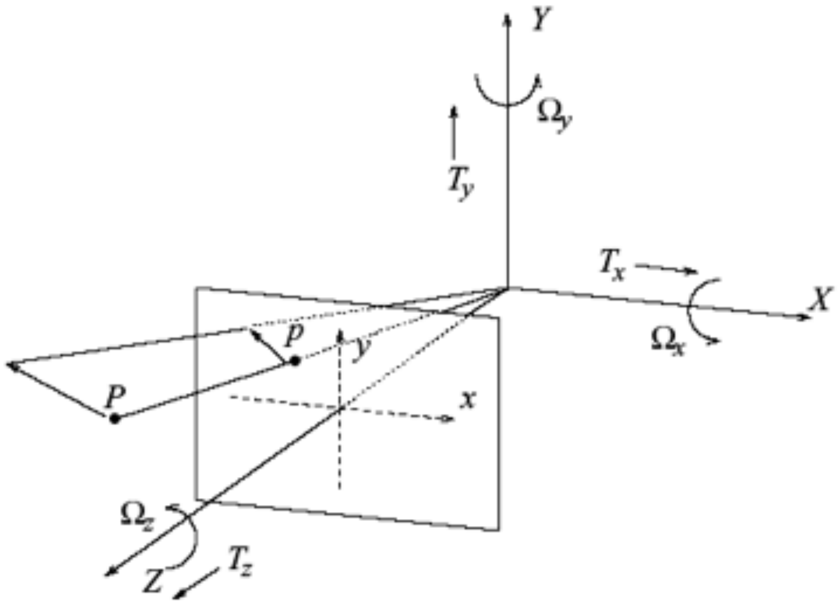


Image Credit: Wikipedia. Optical Flow.

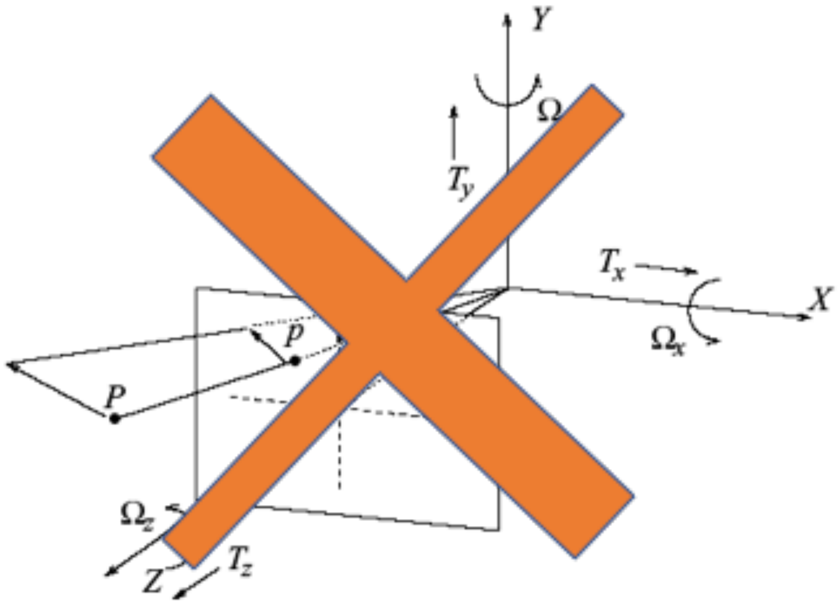
Optical flow - What is it?



Motion field = 2D motion field representing the projection of the 3D motion of points in the scene onto the image plane.

B. Horn, Robot Vision, MIT Press

Optical flow - What is it?

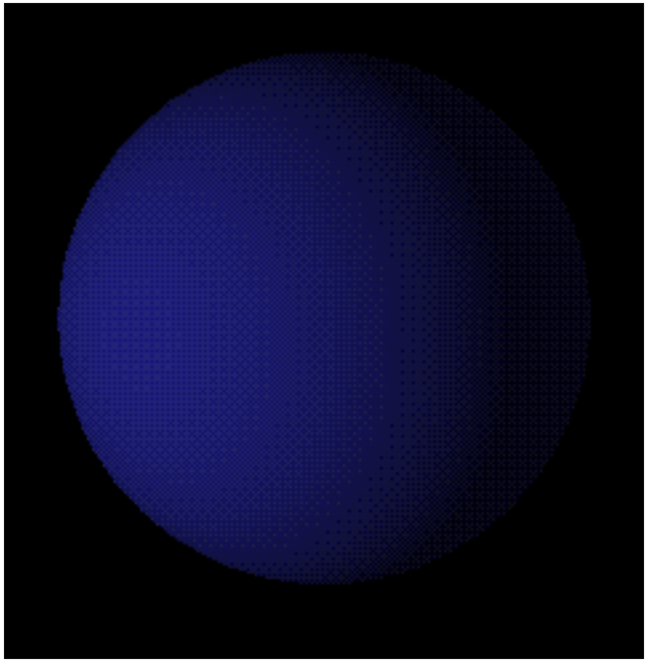


Optical flow = 2D velocity field describing the **apparent** motion in the images.

B. Horn, Robot Vision, MIT Press

What is the motion field? What is the apparent motion?

Lambertian (matte) ball rotating in 3D



What does the 2D motion field look like?

What does the 2D optical flow field look like?

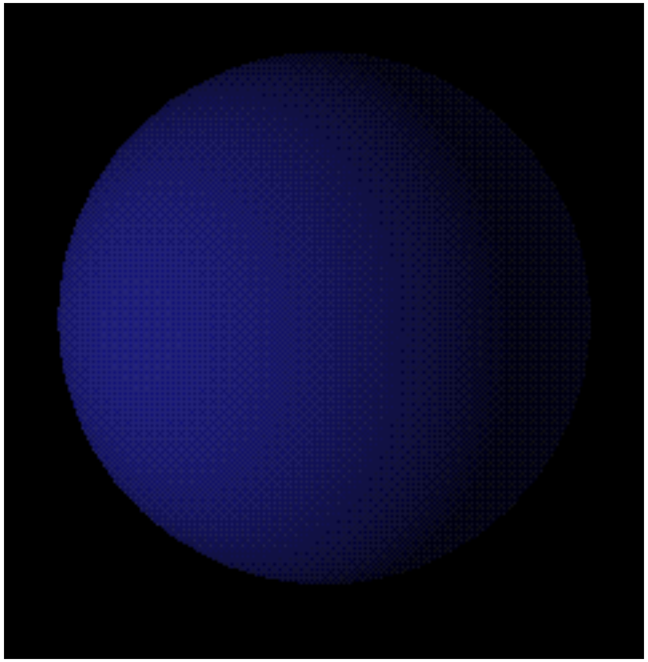
Slide Credit: Michael Black

Image source: http://www.evl.uic.edu/aej/488/lecture12.html

What is the motion field? What is the apparent motion?

Stationary Lambertian (matte) ball

Moving Light Source



What does the 2D motion field look like?

What does the 2D optical flow field look like?

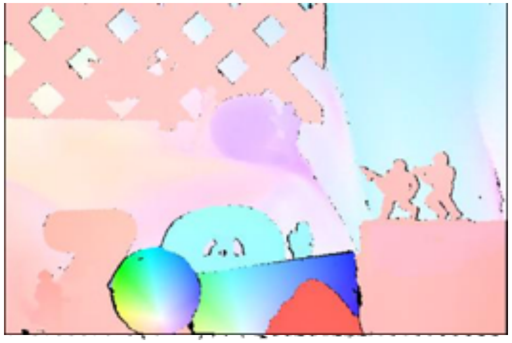
Slide Credit: Michael Black

Image source: http://www.evl.uic.edu/aej/488/lecture12.html

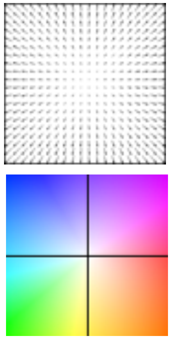
Optical flow - What is it?

Motion Displacement of all image pixels

Image pixel value at time *t* and Location $\mathbf{x} = (x, y)$: $I(x, y, t)$



$u(x, y)$ horizontal component
$v(x, y)$ vertical component

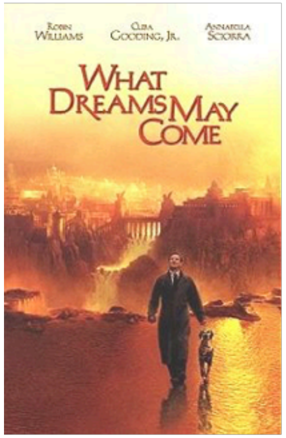


Key

Slide Credit: Michael Black

Optical Flow - What is it good for?

Painterly effect



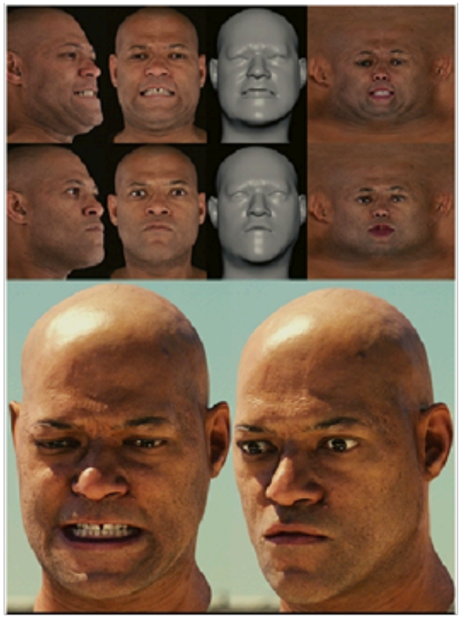
Slide Credit: Michael Black

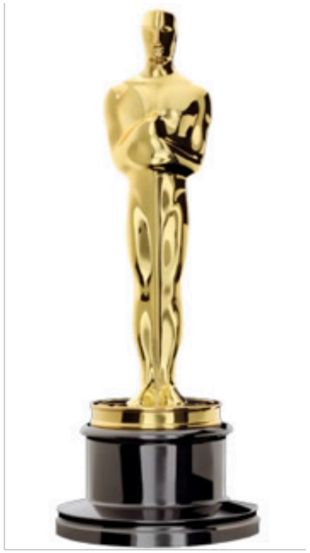
Optical Flow - What is it good for?

Face morphing in matrix reloaded

George Borshukov, Dan Piponi, Oystein Larsen, J.P.Lewis, Christina Tempelaar-Lietz
ESC Entertainment

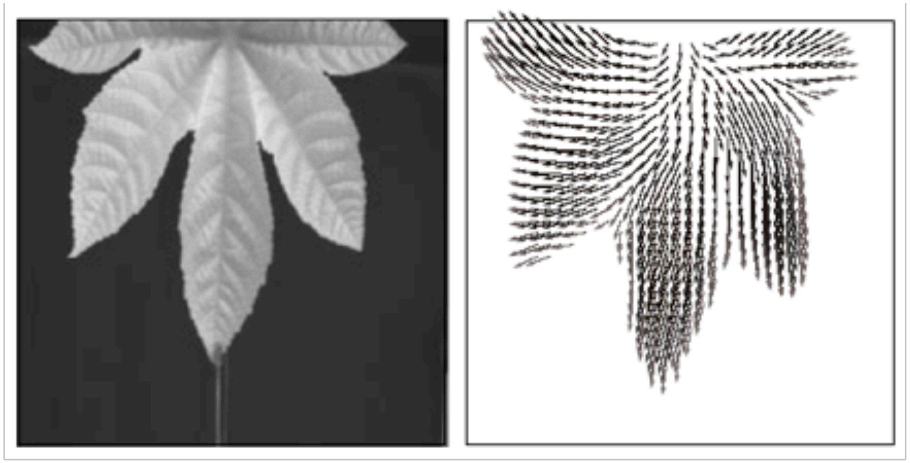
SIGGRAPH'03





Slide Credit: Michael Black

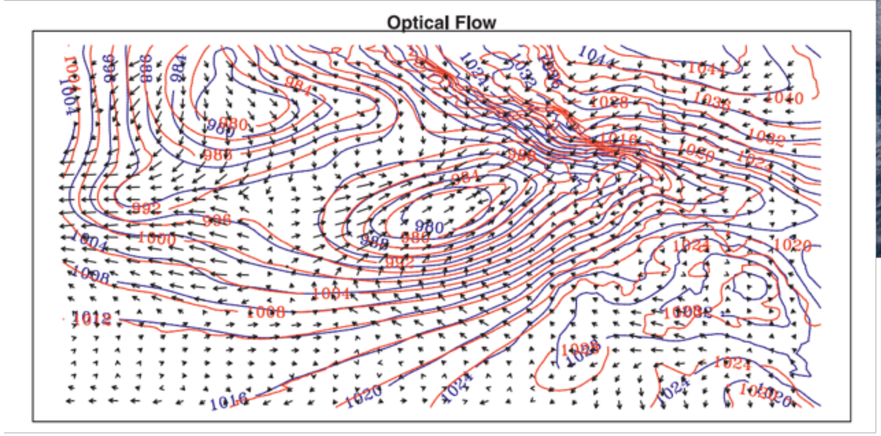
Optical Flow - What is it good for?



Tensor-based Image Sequence Processing Techniques for the Study of Dynamical Processes, Haussecker, Spies, and Jahne, Proc. Intern. Symp. On Real-time Imaging and Dynamic Analysis: 704-711, 1998

Slide Credit: Michael Black

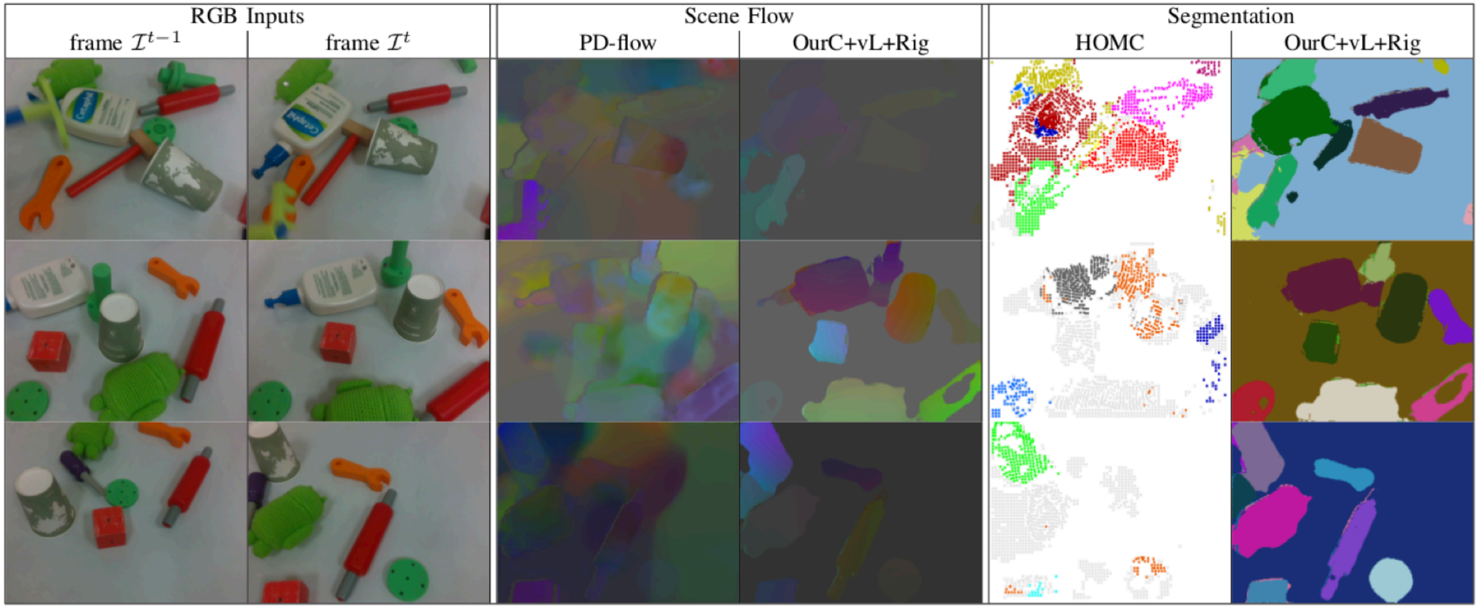
Optical Flow - What is it good for?



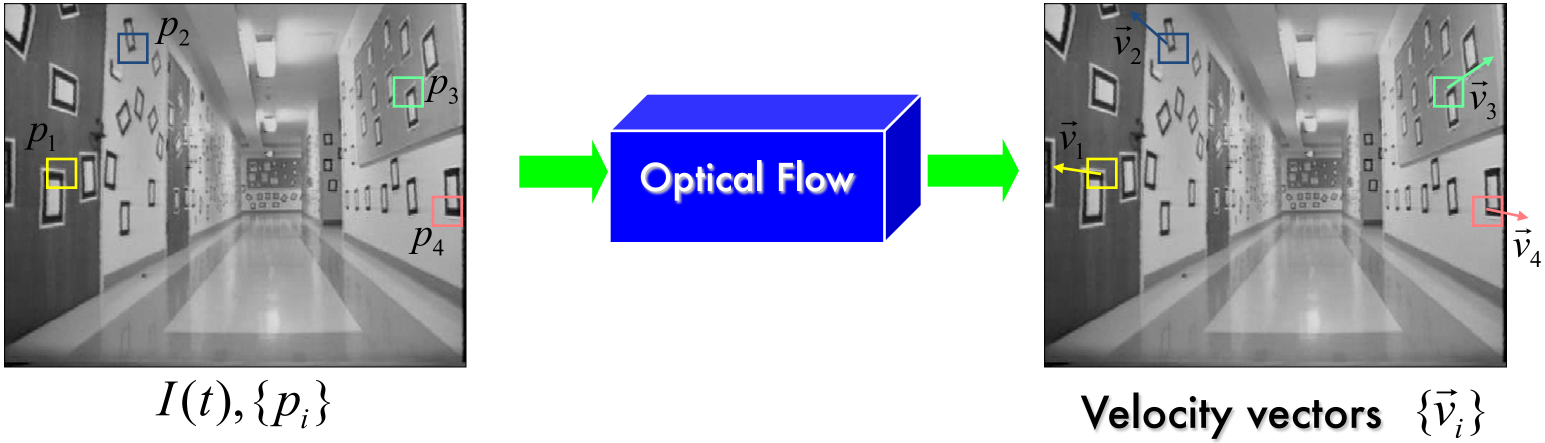
Caren Marzban and Scott Sandgathe
Optical Flow for Verification, Weather and Forecasting, Volume 25 No. 5, October 2010

Slide Credit: Michael Black

Optical Flow - What is it good for?



Optical Flow - What is it good for?



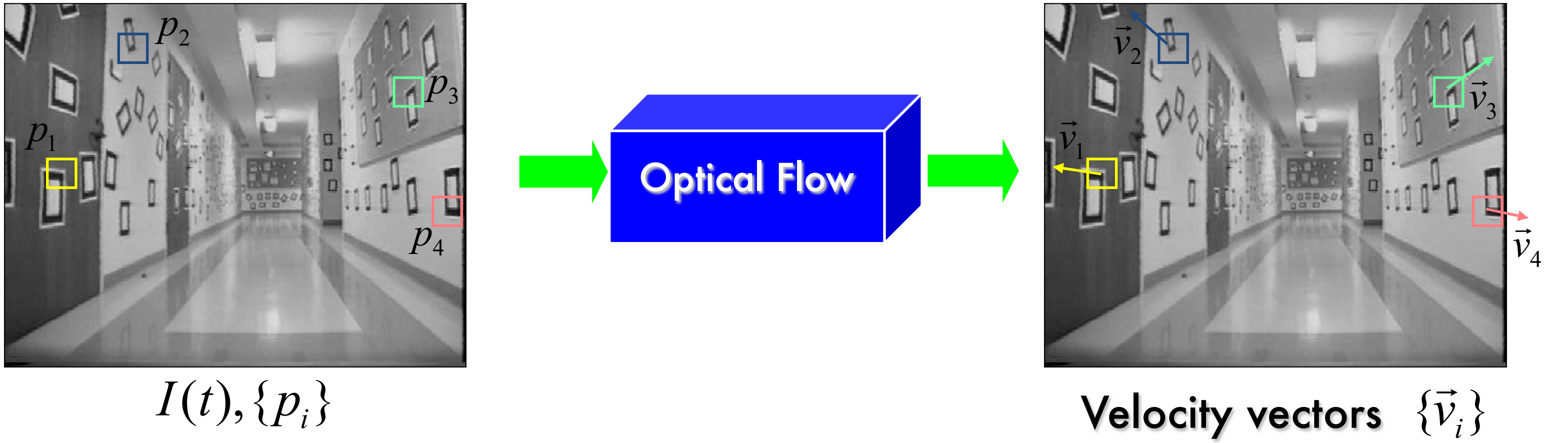
Slide Credit: CS223b – Sebastian Thrun

Compute Optical Flow

Goal

Compute the **apparent** 2D image motion of pixels from one image frame to the next in a video sequence.

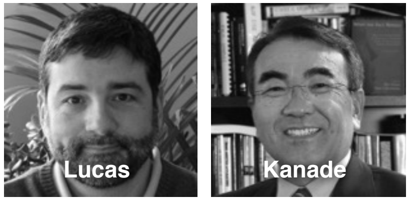
Compute (Sparse) Optical Flow



Simple KLT Tracker

History of the

Kanade-Lucas-Tomasi (KLT) Tracker



An Iterative Image Registration Technique with an Application to Stereo Vision.

1981

Detection and Tracking of Feature Points.

1991

The original KLT algorithm

Good Features to Track.

1994

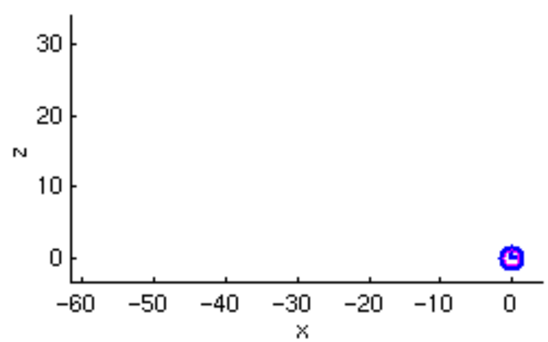
Simple KLT Tracker

1. Find good points to track (Harris corners)
2. For each Harris corner compute motion (translation or affine) between consecutive frames
3. Link motion vector of successive frames to get a track for each Harris point
4. Introduce new Harris points by running detector every 10-15 frames
5. Track old and new corners using step 1-3

Computing (Sparse) Optical Flow

$I(t), \{p_i\}$

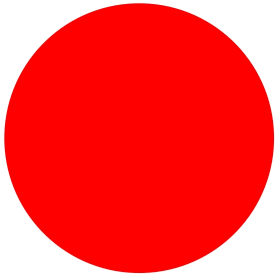
Velocity vectors $\{\vec{v}_i\}$



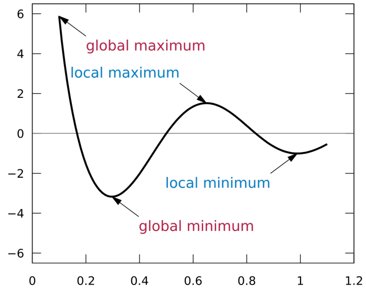
Jean-Yves Bouguet, Ph.D. CalTech

Compute (Dense) Optical Flow

Step 1 - Assumptions



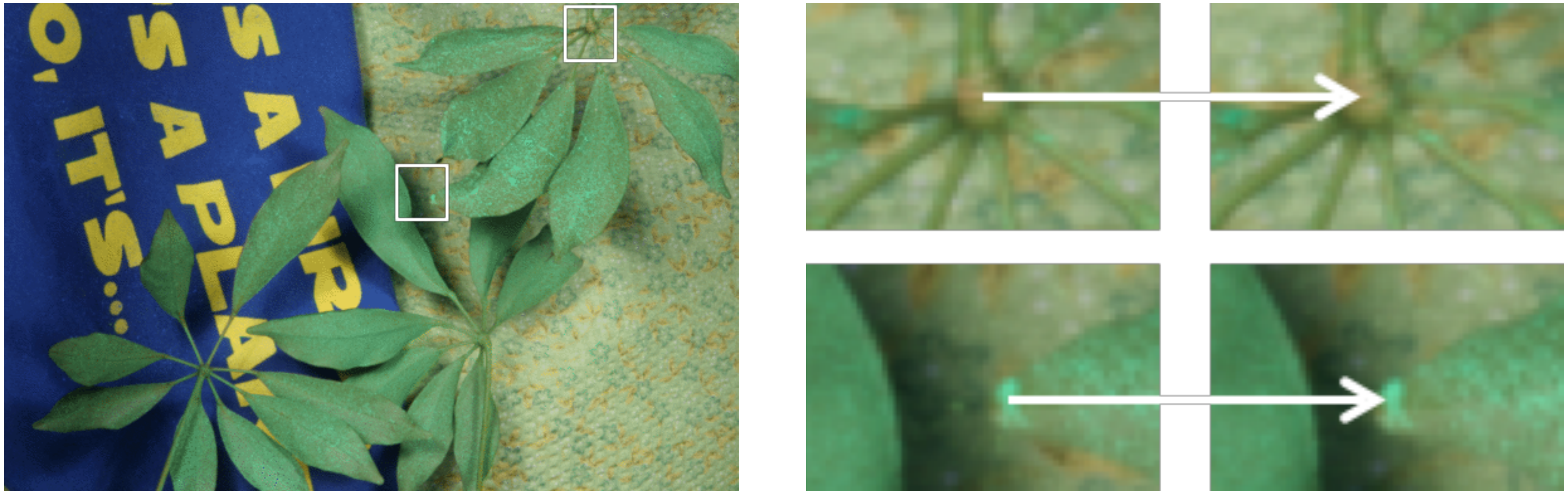
Step 2 - Objective Function



Source: Wikipedia.

Step 3 - Optimization

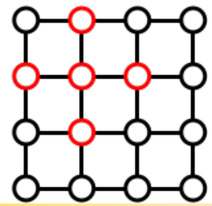
Assumption 1 - Brightness Constancy



$$I(x+u, y+v, t+1) = I(x, y, t)$$

Slide Credit: Michael Black

Assumption 2 - Spatial Smoothness



Slide Credit: Michael Black

Assumption 3 – Temporal Coherence

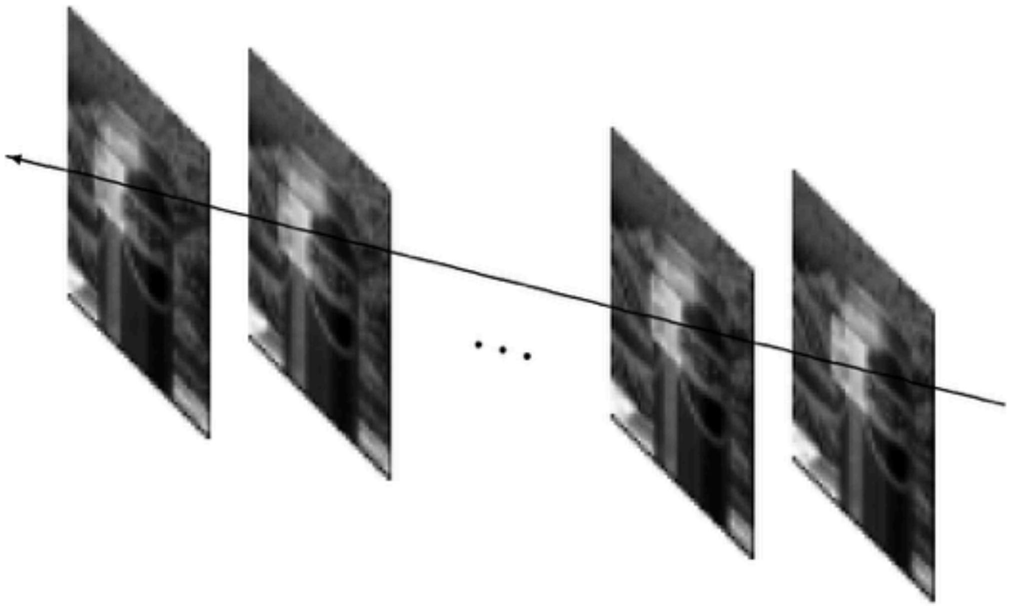
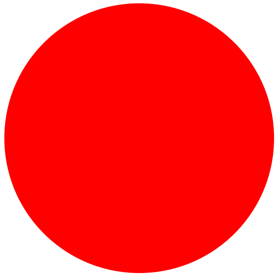


Figure 1.8: Temporal continuity assumption. A patch in the image is assumed to have the same motion (constant velocity, or acceleration) over time.

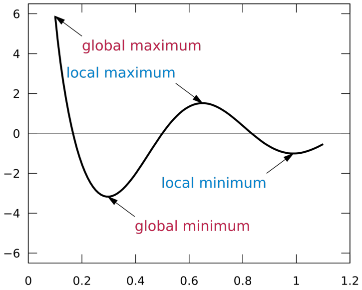
Slide Credit: Michael Black

Compute Optical Flow

Step 1 - Assumptions



Step 2 - Objective Function



Source: Wikipedia.

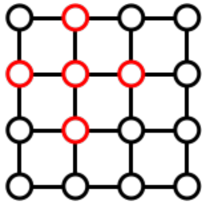
Objective Function

$$E_D(\mathbf{u},\mathbf{v}) = \sum_s (I(x_s + u_s, y_s + v_s, t+1) - I(x,y,t))^2$$

New Assumption: Gaussian noise

Objective Function

$$E_S(\mathbf{u},\mathbf{v}) = \sum_{n \in G(s)} (u_s - u_n)^2 + \sum_{n \in G(s)} (v_s - v_n)^2$$



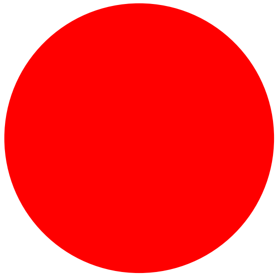
New Assumptions:
Flow field smooth
Gaussian Deviations
First order smoothness good enough
Flow derivative approximated by first differences

Objective Function

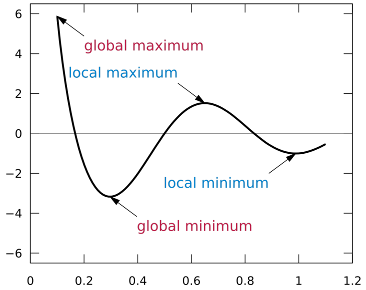
$$E(u,v) = \sum_s (I(x_s + u_s, y_s + v_s, t+1) - I(x,y,t))^2 + \lambda\left(\sum_{n \in G(s)} (u_s - u_n)^2 + \sum_{n \in G(s)} (v_s - v_n)^2\right)$$

Compute Optical Flow

Step 1 - Assumptions



Step 2 - Objective Function



Source: Wikipedia.

Step 3 - Optimization

Linear Approximation

$$E(u,v) = \sum_s (I(x_s + u_s, y_s + v_s, t+1) - I(x,y,t))^2 + \lambda\left(\sum_{n \in G(s)} (u_s - u_n)^2 + \sum_{n \in G(s)} (v_s - v_n)^2\right)$$

$$u_s = dx, v_s = dy, dt = 1$$

$$I(x,y,t) + dx\frac{\delta}{\delta x}I(x,y,t) + dy\frac{\delta}{\delta y}I(x,y,t) + dt\frac{\delta}{\delta t}I(x,y,t) - I(x,y,t) = 0$$

Optical Flow Constraint Equation

$$u\frac{\delta}{\delta x}I(x,y,t) + v\frac{\delta}{\delta y}I(x,y,t) + \frac{\delta}{\delta t}I(x,y,t) = 0$$

$$I_x u + \ I_y v + \ I_t = 0$$

New Assumptions:
Flow is small
Image is differentiable
First order Taylor series is a good approximation

Optical Flow Constraint Equation

Notation

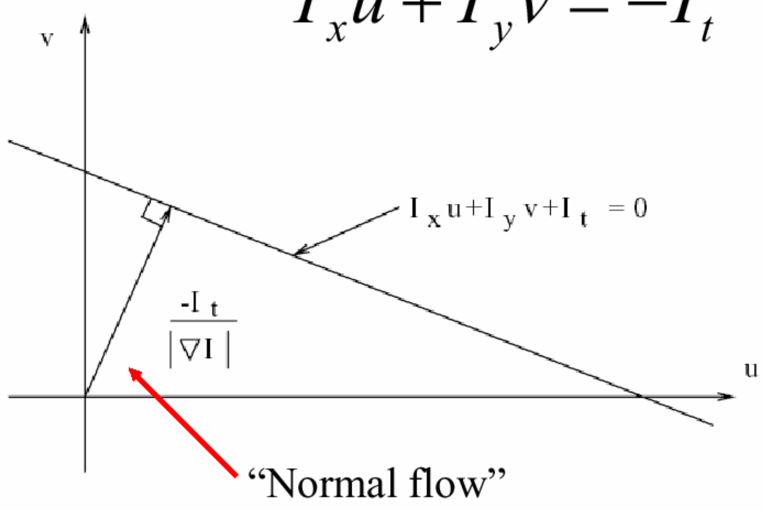
$$I_x u + I_y v + I_t = 0$$

$$\nabla I^T \mathbf{u} = -I_t$$

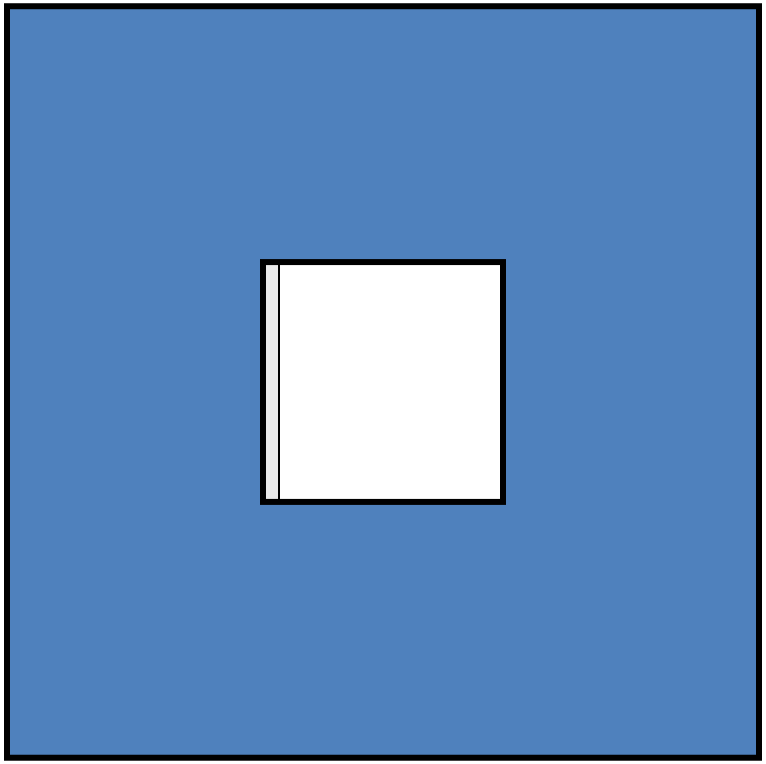
$$\mathbf{u} = \begin{bmatrix} u \\ v \end{bmatrix} \quad \nabla I = \begin{bmatrix} I_x \\ I_y \end{bmatrix}$$

At a single image pixel, we get a line:

$$I_x u + I_y v = -I_t$$

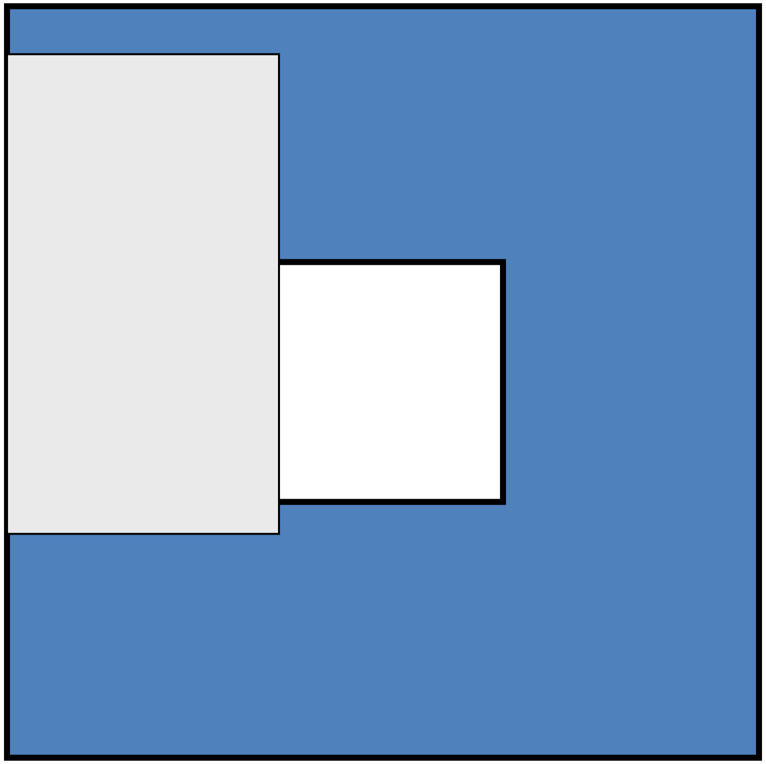


Aperture Problem



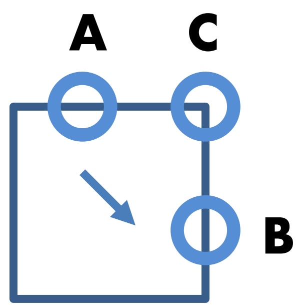
Slide Credit: CS223b – Sebastian Thrun

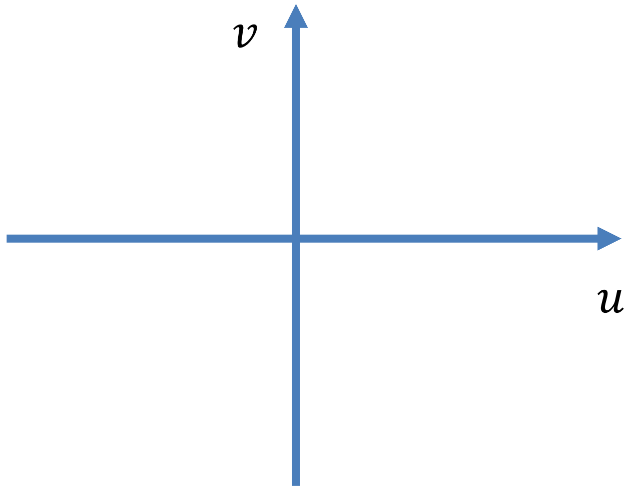
Aperture Problem



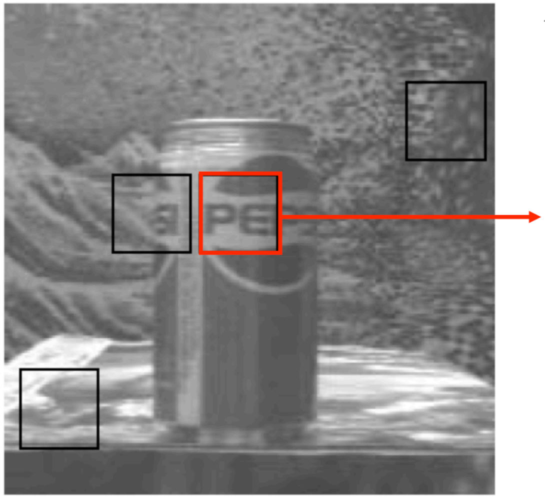
Slide Credit: CS223b – Sebastian Thrun

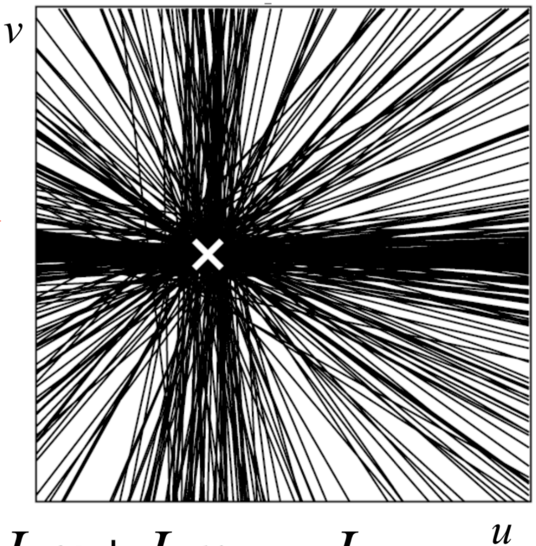
What are the constraint lines?





Multiple Constraints





Each pixel gives us a constraint: $I_x u + I_y v = -I_t$

Slide Credit: Michael Black

How do we solve this optimization problem?

$$E(u,v) = \sum_{x,y \in R} (I_x(x,y,t)u + I_y(x,y,t)v + I_t(x,y,t))^2$$

$$\frac{\partial E}{\partial u} = \sum_R (I_x u + I_y v + I_t) I_x = 0$$

$$\frac{\partial E}{\partial v} = \sum_R (I_x u + I_y v + I_t) I_y = 0$$

How do we solve this optimization problem?

$$\left[\sum_R I_x^2\right]u + \left[\sum_R I_x I_y\right]v = -\sum_R I_x I_t$$

$$\left[\sum_R I_x I_y\right]u + \left[\sum_R I_y^2\right]v = -\sum_R I_y I_t$$

$$\begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_y I_x & \sum I_y^2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} -\sum I_x I_t \\ -\sum I_y I_t \end{bmatrix}$$

How do we solve this optimization problem?

$$\begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_y I_x & \sum I_y^2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} -\sum I_x I_t \\ -\sum I_y I_t \end{bmatrix}$$

$$\mathbf{A}\mathbf{u} = \mathbf{b}$$

How do we solve this optimization problem?

$$\mathbf{A}^{-1}\mathbf{A}\mathbf{u} = \mathbf{A}^{-1}\mathbf{b}$$

$$\mathbf{u} = \mathbf{A}^{-1}\mathbf{b}$$

$$\mathbf{u} = \begin{bmatrix} u \\ v \end{bmatrix} \quad \nabla I = \begin{bmatrix} I_x \\ I_y \end{bmatrix}$$

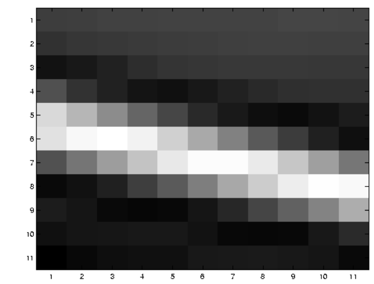
$$\mathbf{u} = -\left(\sum \nabla I \nabla I^T\right)^{-1} \sum \nabla I I_t$$

$$\mathbf{A}\mathbf{u} = \mathbf{b}$$

$$\mathbf{A}^T\mathbf{A}\mathbf{u} = \mathbf{A}^T\mathbf{b}$$

$$\mathbf{u} = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{b}$$

Image Gradient Examples - Edge



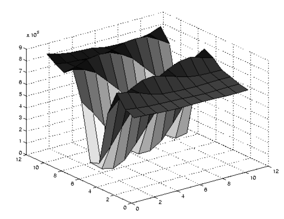
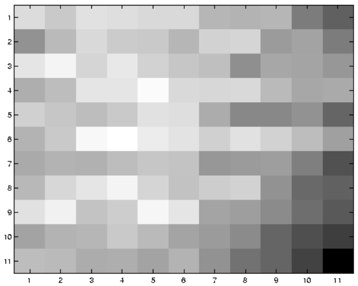


Image Gradient Examples – Low texture



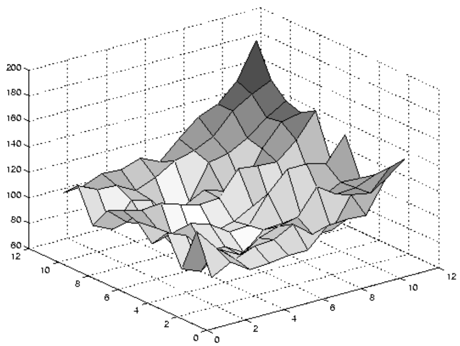
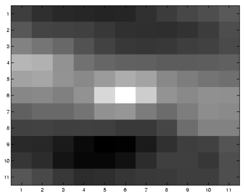
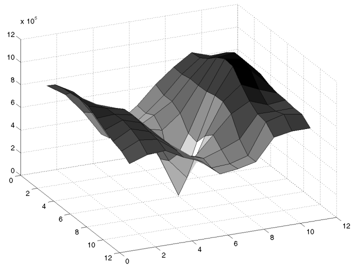


Image Gradient Examples – Low texture



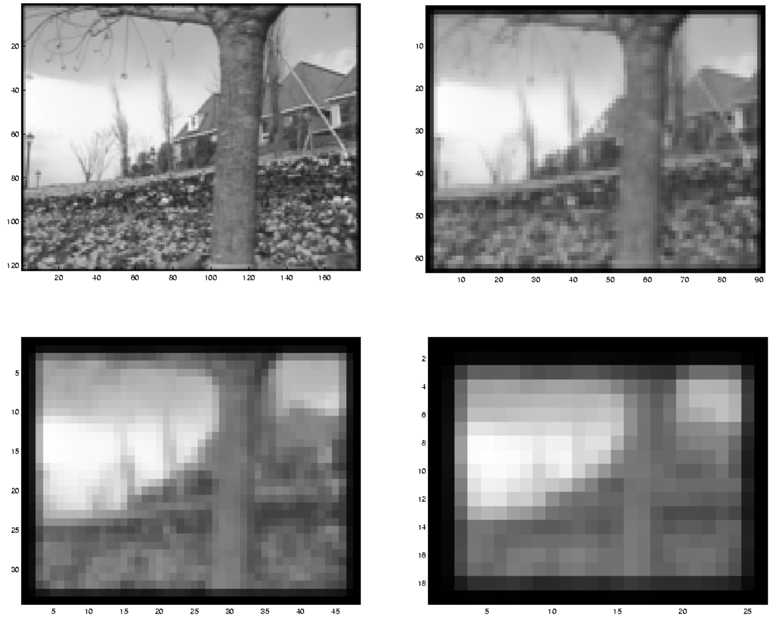


Bag of tricks

Small motion assumption

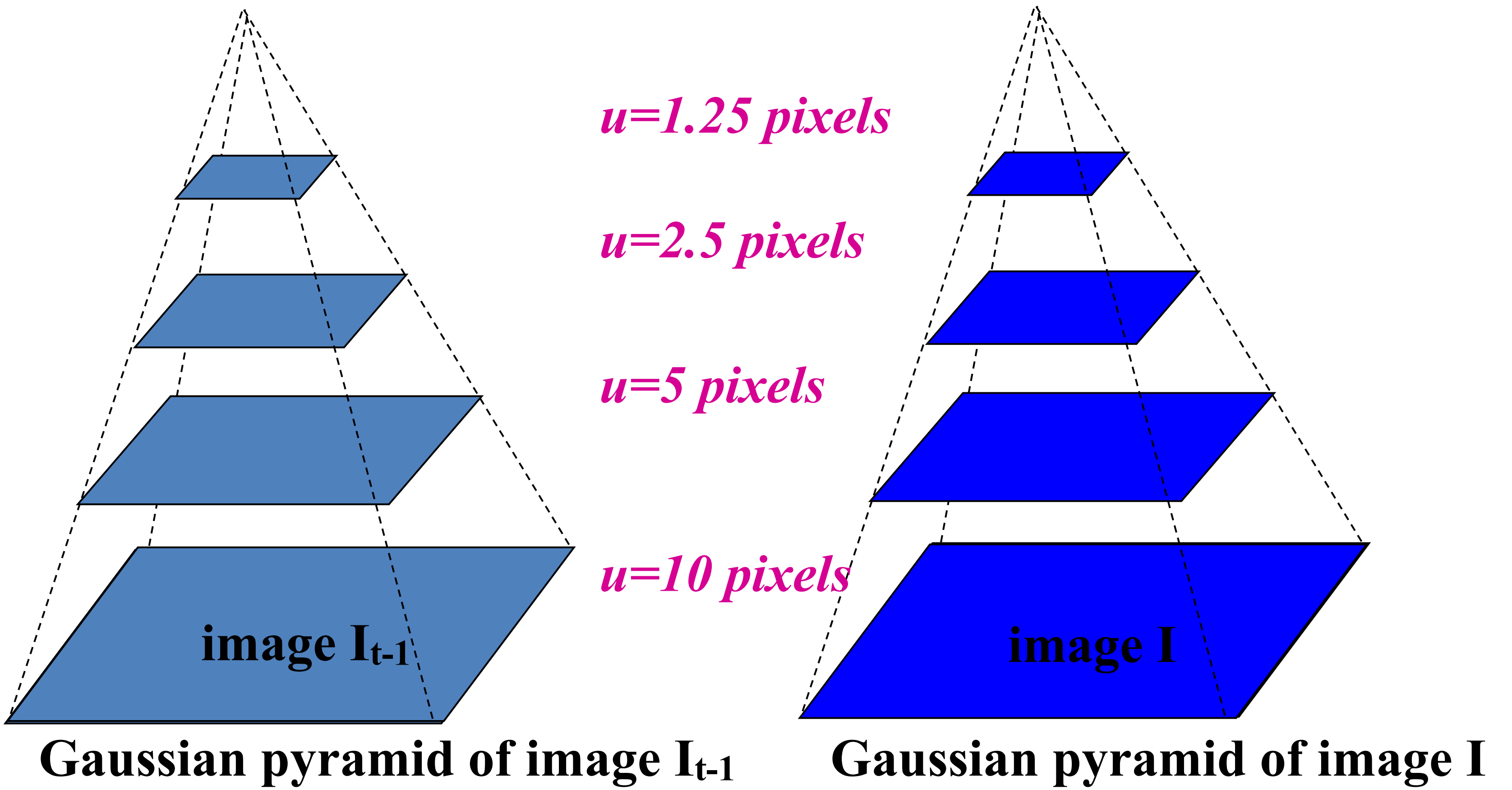
Bag of tricks

Reduce Resolution

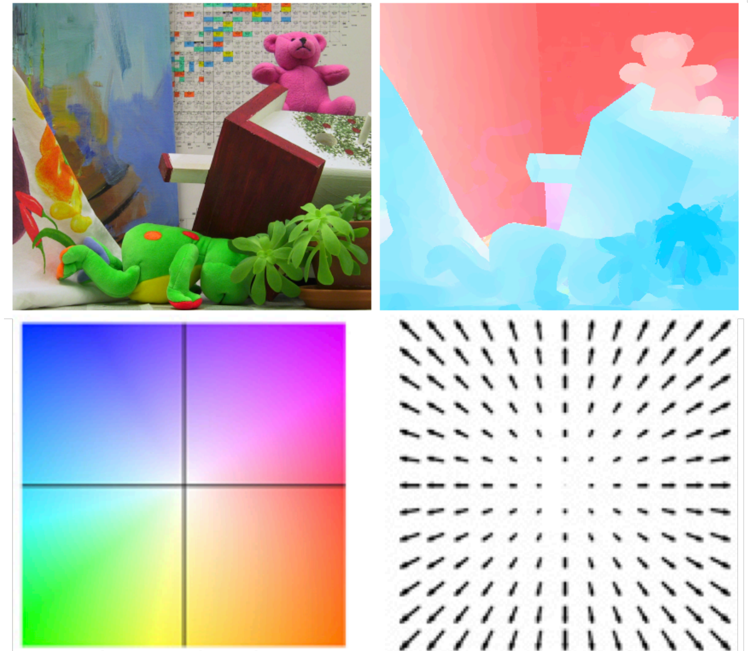


* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

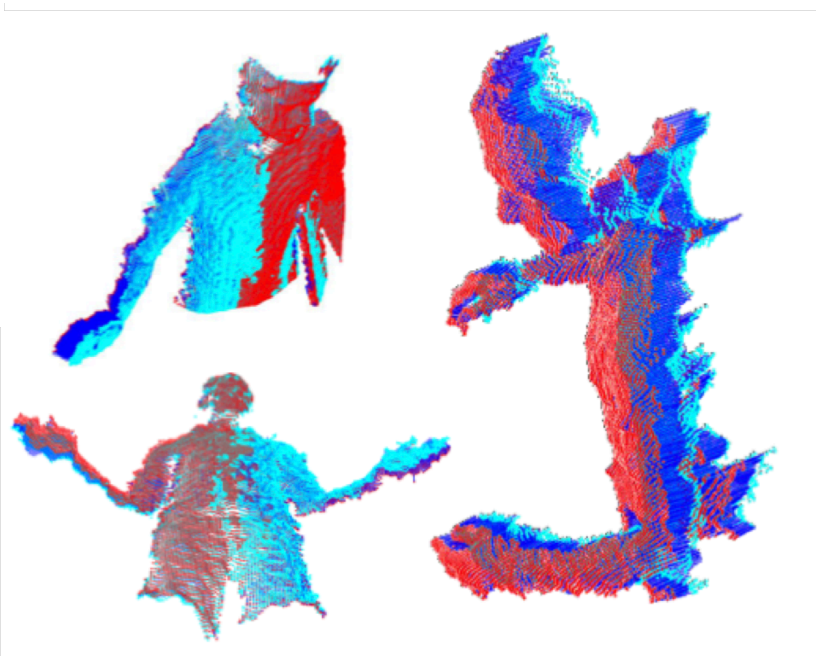
Spatial Pyramides



Scene Flow



A Database and Evaluation Methodology for Optical Flow. Baker et al. IJCV. 2011



A Primal-Dual Framework for Real-Time Dense RGB-D Scene Flow. Jaimez at al. ICRA, 2015.

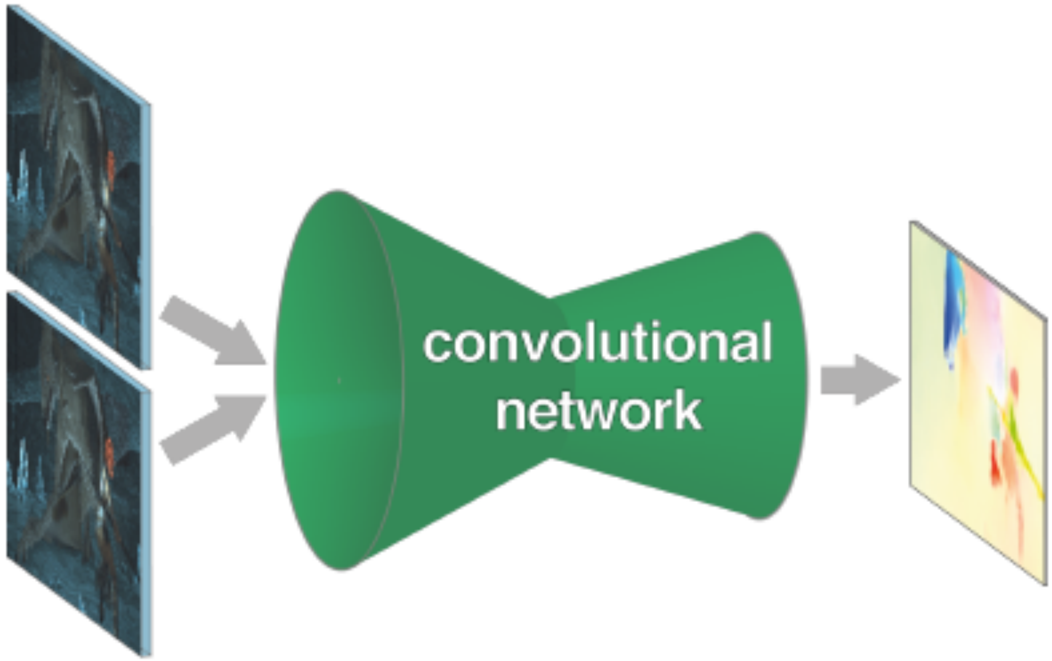
What are the main challenges with this traditional formulation?

- Assumptions
  - Brightness constancy
  - Small motion
  - Etc
- Occlusions
- Large motion

Learning-based approaches

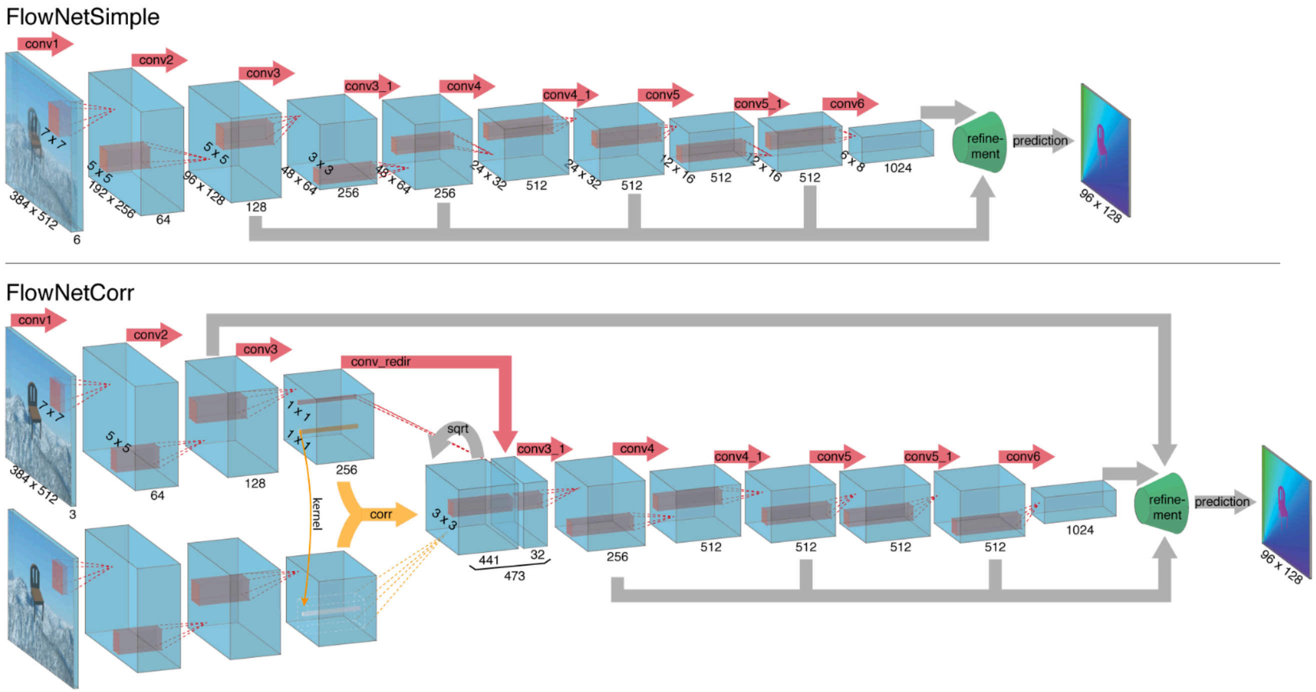
- Since 2015
- Availability of data

FlowNet - **Learning Optical Flow with Convolutional Networks**



Alexey Dosovitskiy, Philipp Fischer, Eddy Ilg, P. Häusser, C. Hazırbaş, V. Golkov, P. Smagt, D. Cremers, Thomas Brox. IEEE International Conference on Computer Vision (ICCV), 2015

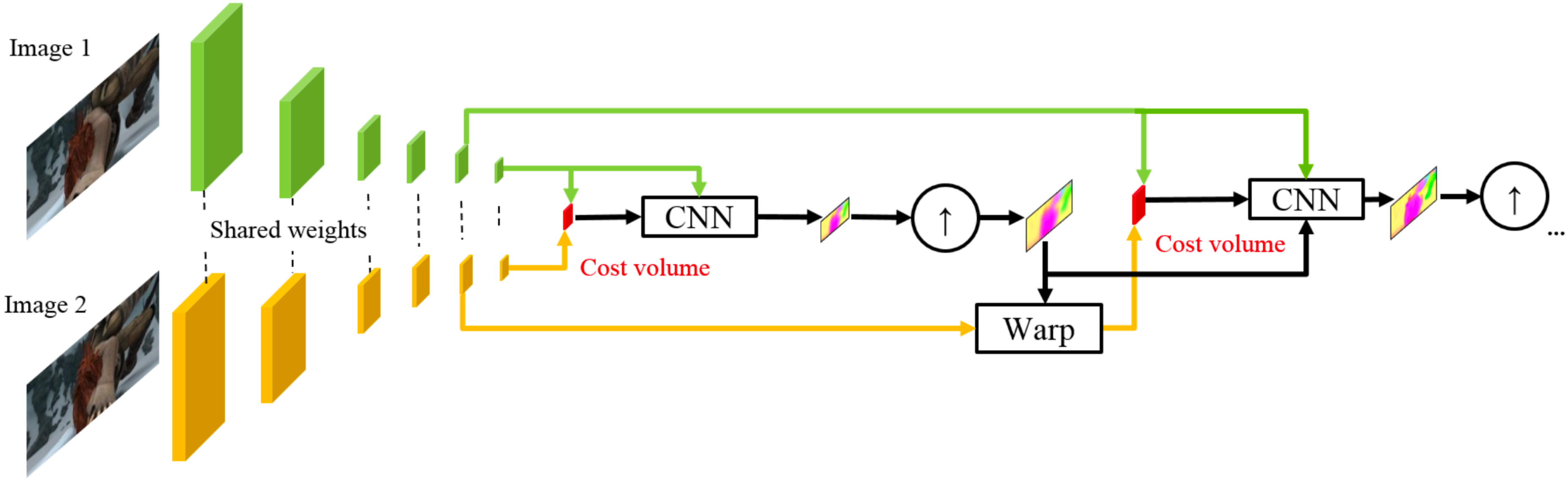
FlowNet - **Learning Optical Flow with Convolutional Networks**



Supervised Learning

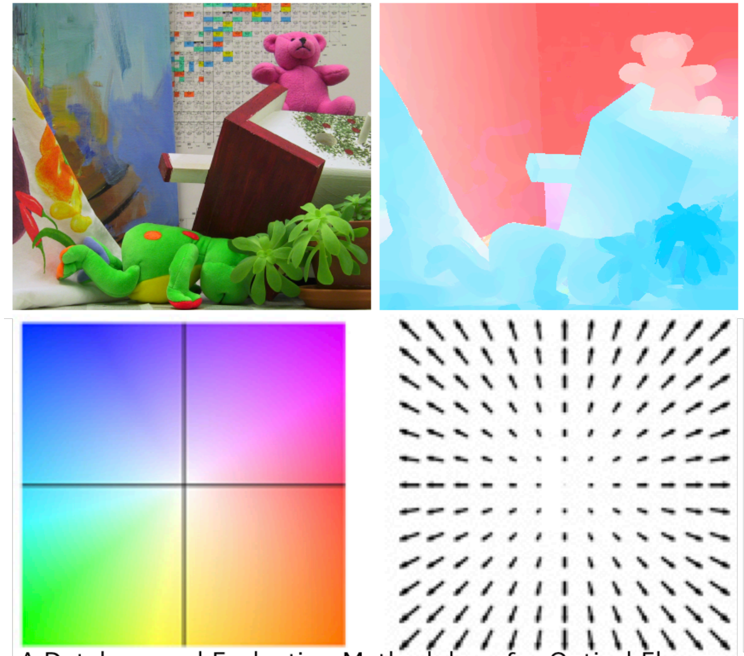
Supervised Optical Flow using traditional principles

Pyramidal Processing, Image Warping & Cost volume processing

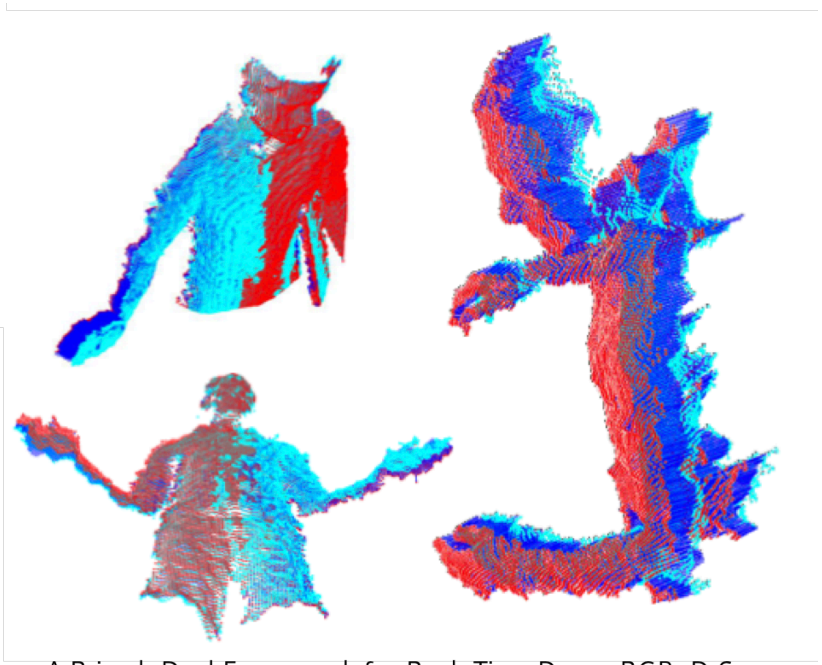


Deqing Sun, Xiaodong Yang, Ming-Yu Liu, and Jan Kautz. "PWC-Net: CNNs for Optical Flow Using Pyramid, Warping, and Cost Volume." CVPR 2018

Scene Flow

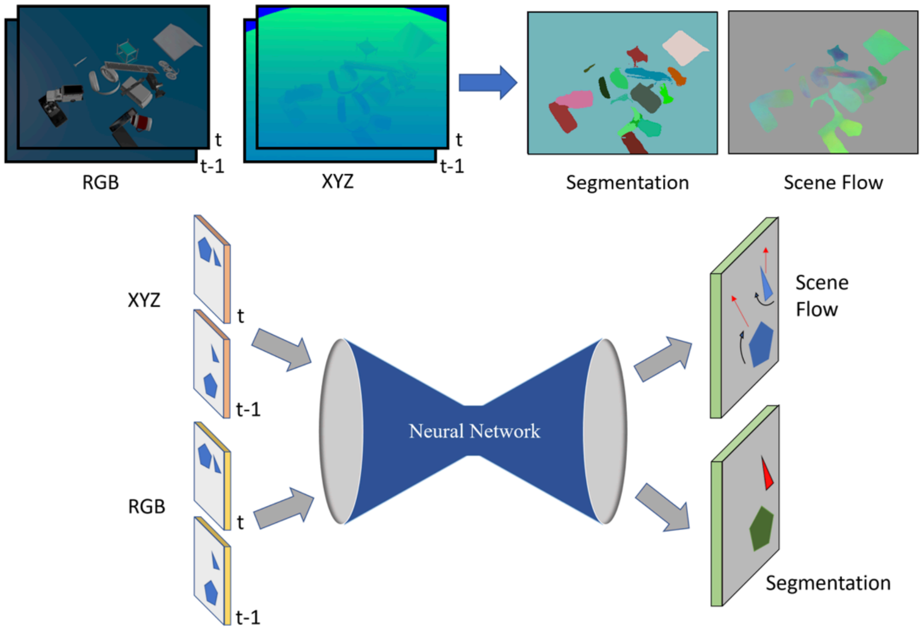


A Database and Evaluation Methodology for Optical Flow. Baker et al. IJCV. 2011

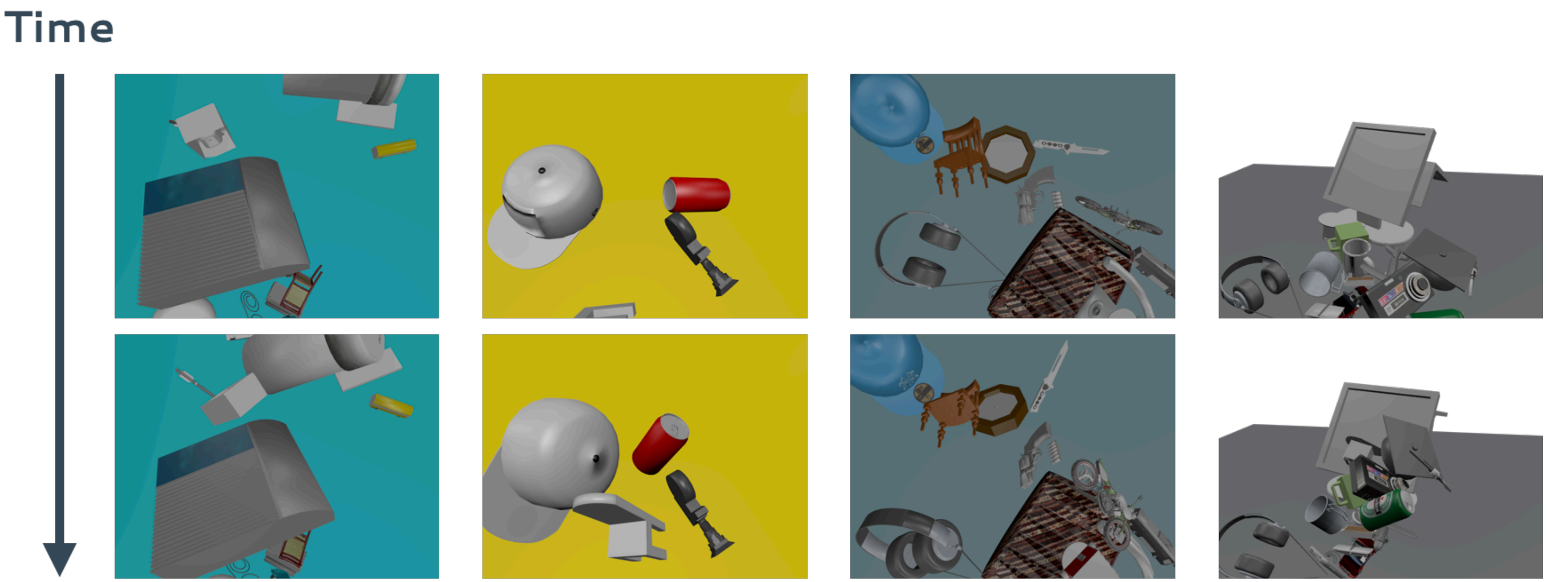


A Primal-Dual Framework for Real-Time Dense RGB-D Scene Flow. Jaimez at al. ICRA, 2015.

Motion-based Object Segmentation based on Dense RGB-D Scene Flow

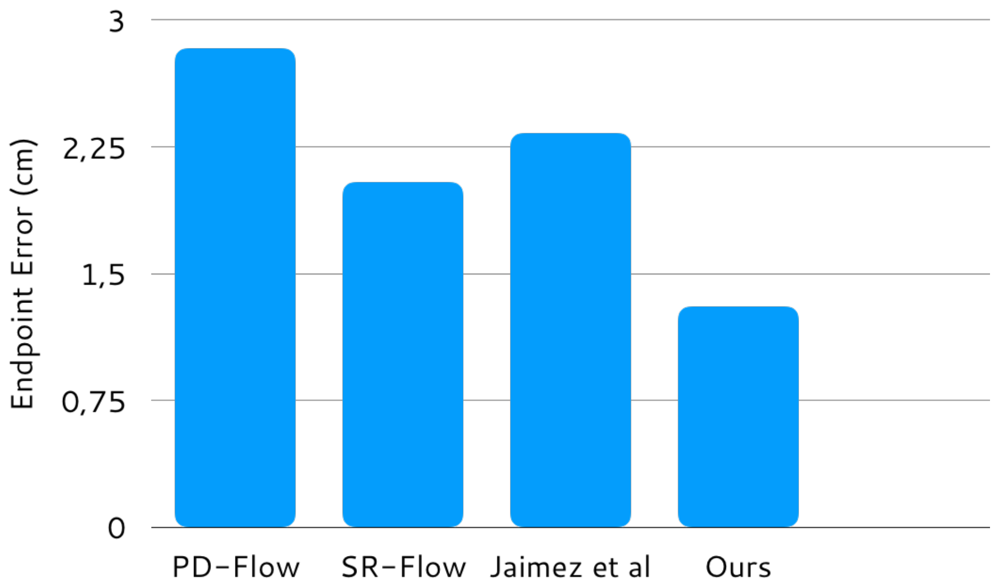


Motion-based Object Segmentation based on Dense RGB-D Scene Flow

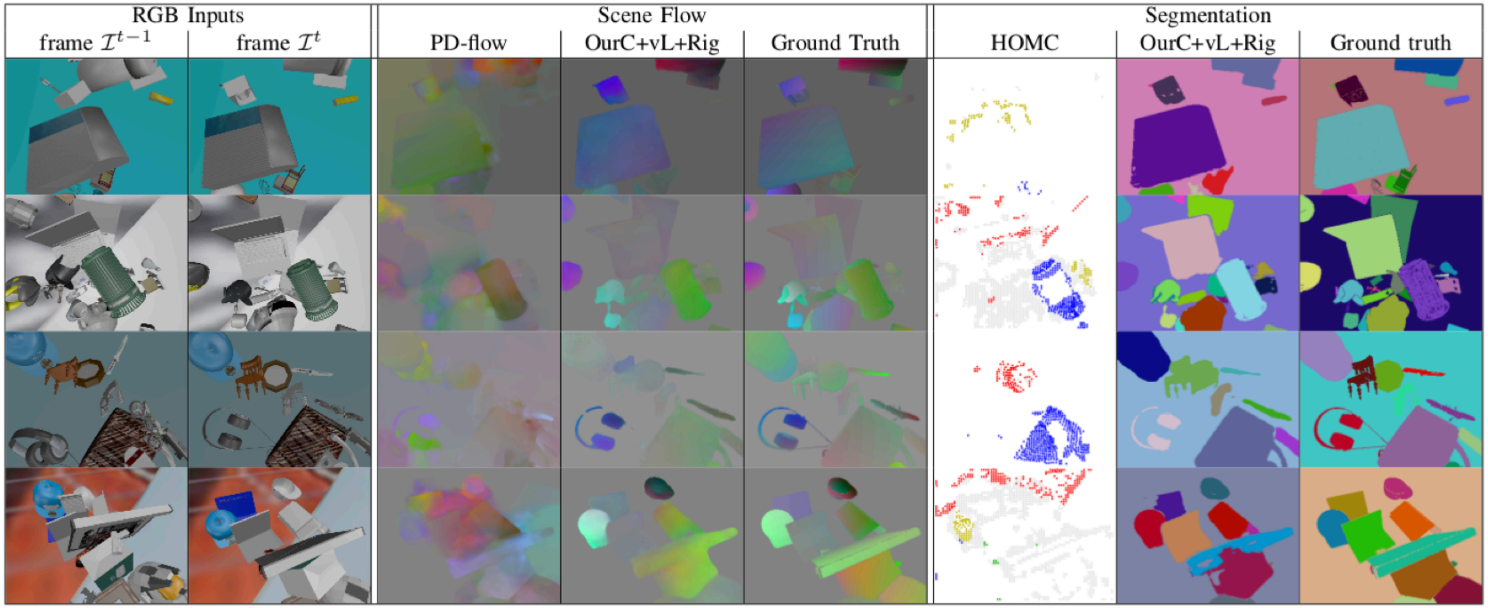


Motion-based Object Segmentation based on Dense RGB-D Scene Flow. Shao et al. RAL + IROS. 2018. Pre-print on arXiv.

Motion-based Object Segmentation based on Dense RGB-D Scene Flow

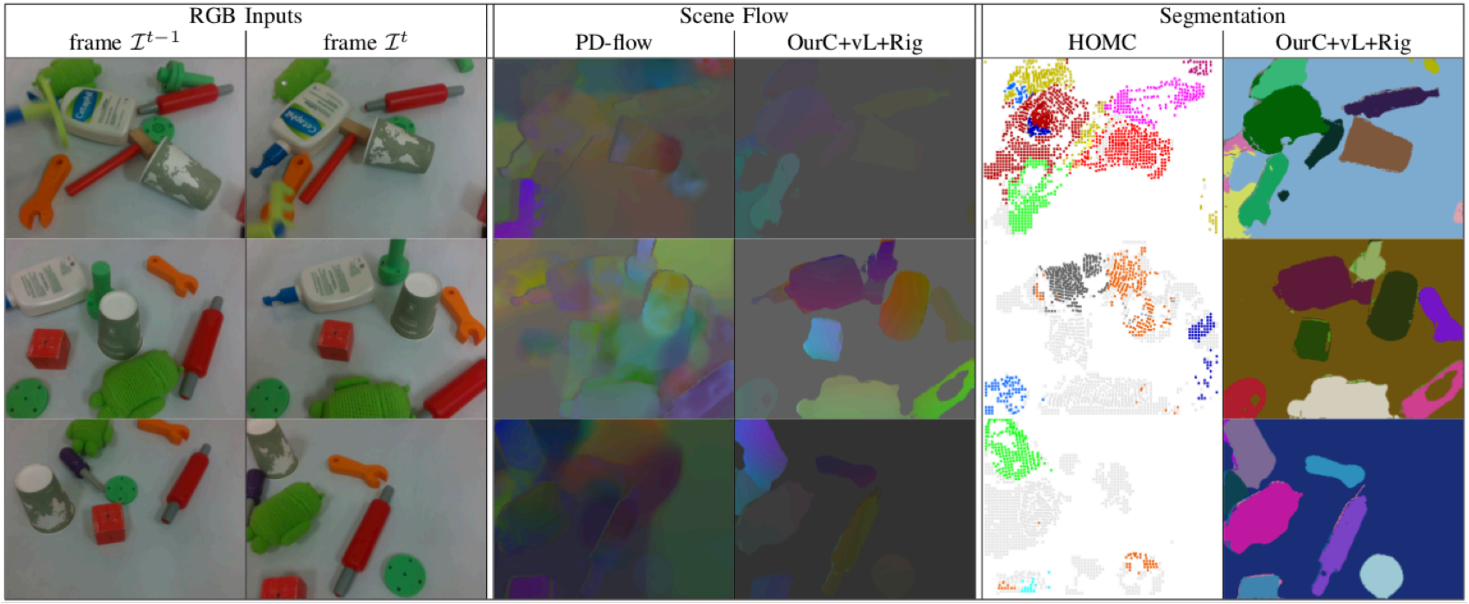


Motion-based Object Segmentation based on Dense RGB-D Scene Flow



Motion-based Object Segmentation based on Dense RGB-D Scene Flow. Shao et al. RAL + IROS. 2018. Pre-print on arXiv.

Motion-based Object Segmentation based on Dense RGB-D Scene Flow



Motion-based Object Segmentation based on Dense RGB-D Scene Flow. Shao et al. RAL + IROS. 2018. Pre-print on arXiv.

CS231

Introduction to Computer Vision

Next lecture:

Optimal Recursive Estimation