ADVANCES IN COMPUTER VISION

MODULE 1: Geometry

CORRESPONDENCE I: OPTICAL FLOW



Prof. Vincent Sitzmann

Credits

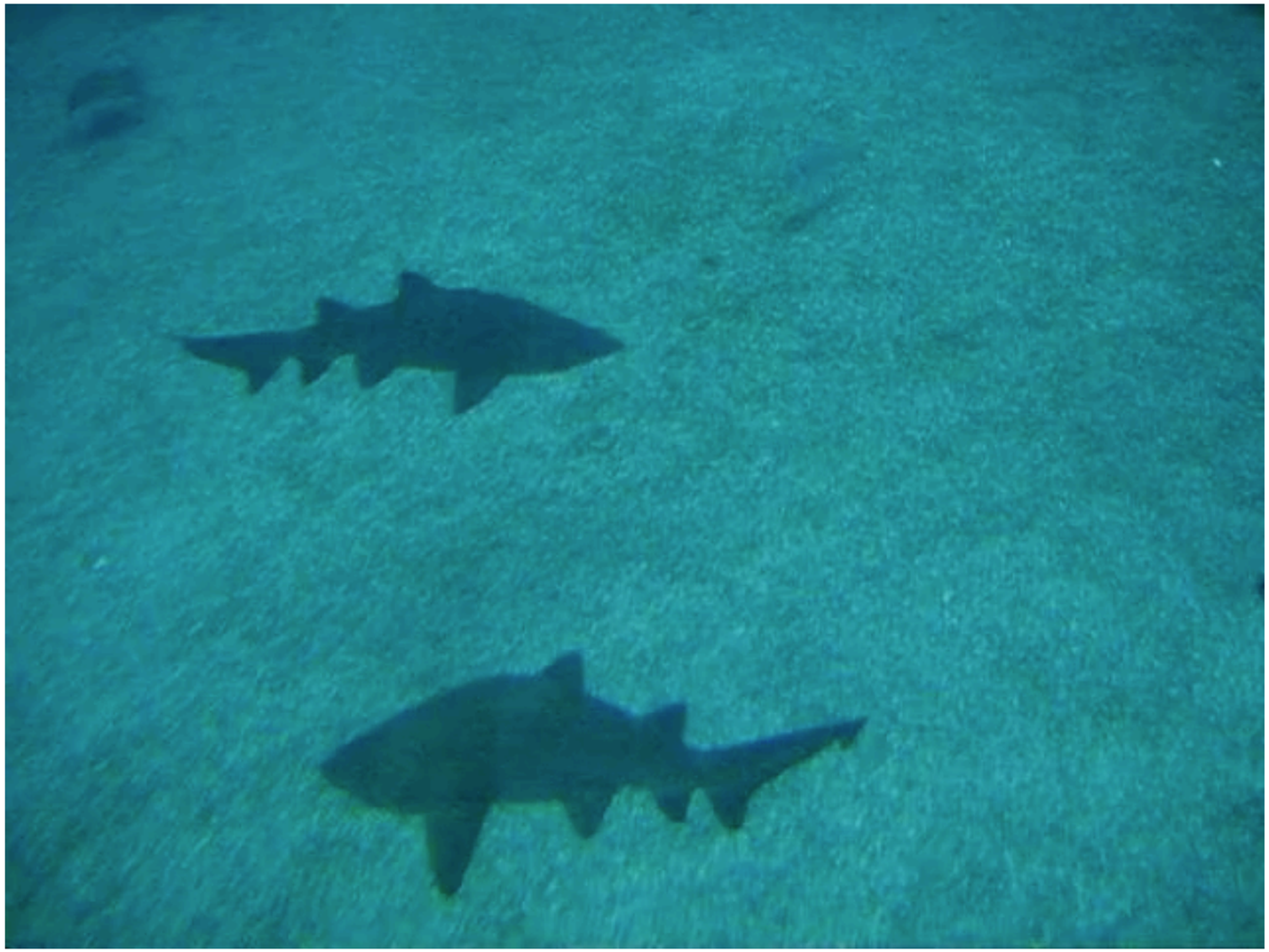
Base of this lecture: Deqing Sun & Charles Herrmann

Some slides, images, and videos from
- Dr. Ce Liu@Microsoft
- Dr. Huaizu Jiang@Northeastern
- Dr. David Fouhey@UMich
- Dr. Justin Johnson@UMich
- Dr. Svetlana Lazebnik@UIUC
- Dr. Shree K. Nayar@Columbia
- Dr. Jia Deng@Princeton
- Dr. Ming-Hsuan Yang@UC Merced
- Dr. Rick Szeliski's book
- Book by Antonio, Phillip, and Bill
- Dr. Christian Rupprecht@Oxford

Suggestions from Dr. Bill Freeman, Dr. Rick Szeliski, Dr. Noah Snavely and Dr. Junhwa Hur

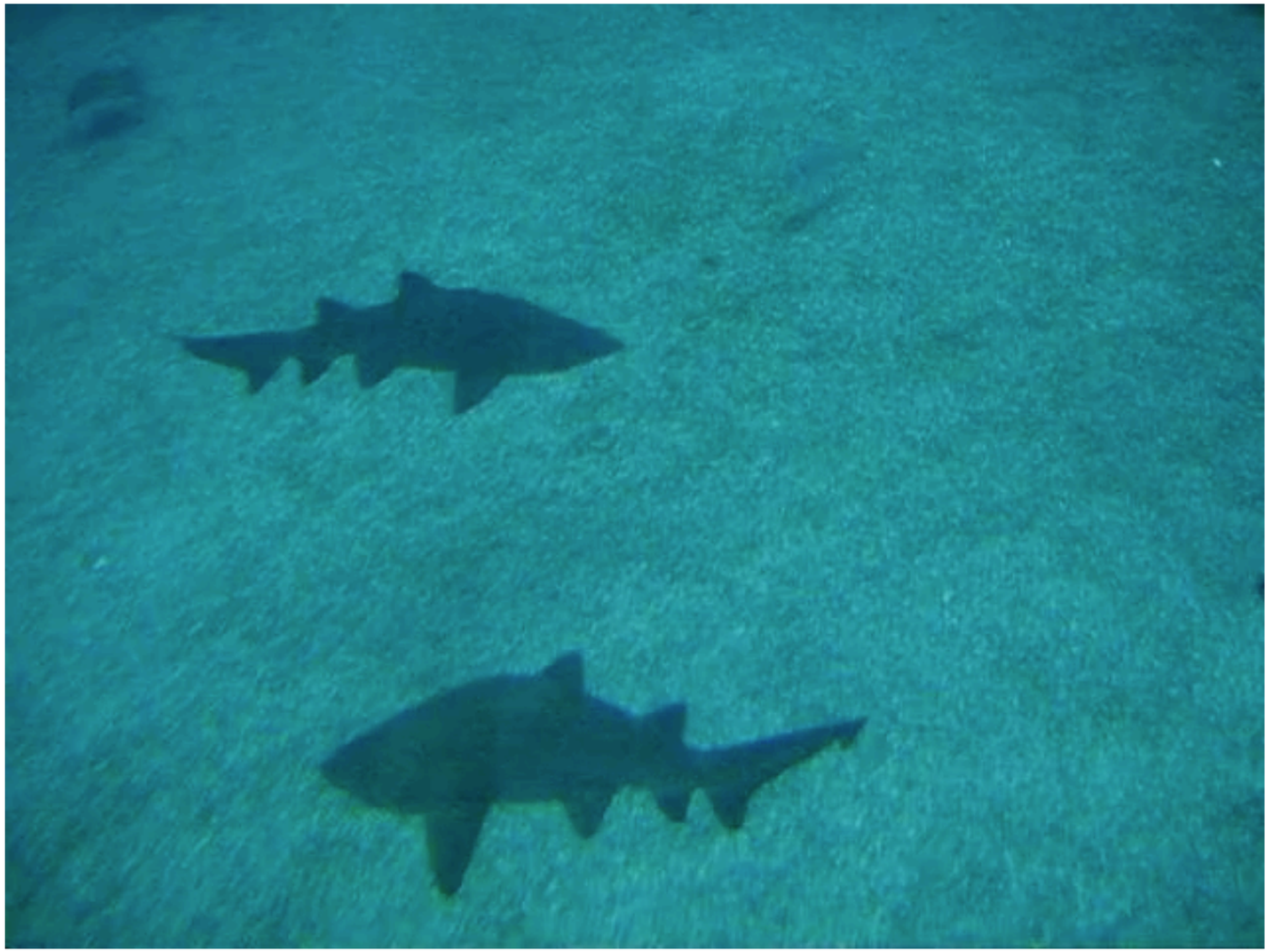
We live in a dynamic world

Perceiving, understanding and predicting motion is an important part of our daily lives



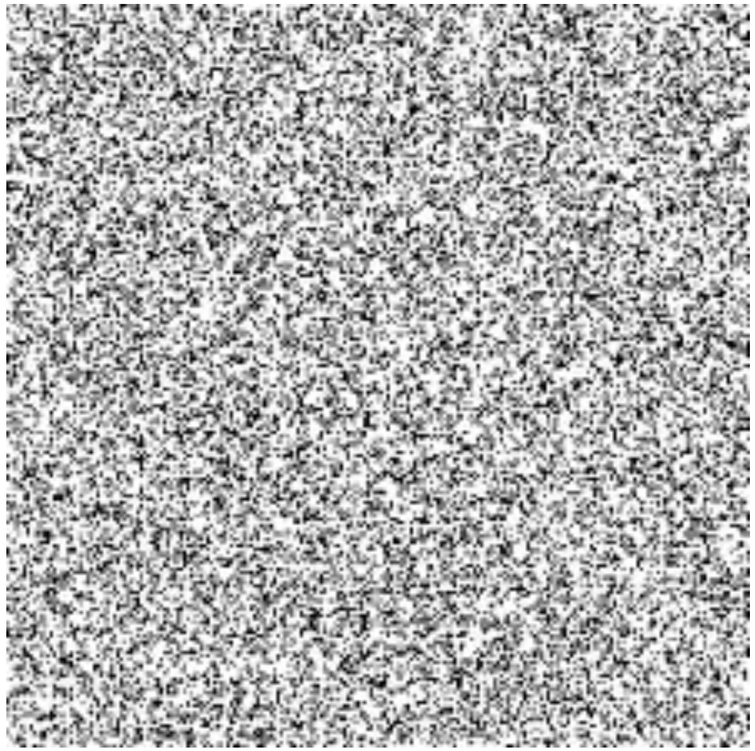
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Motion and perceptual organization

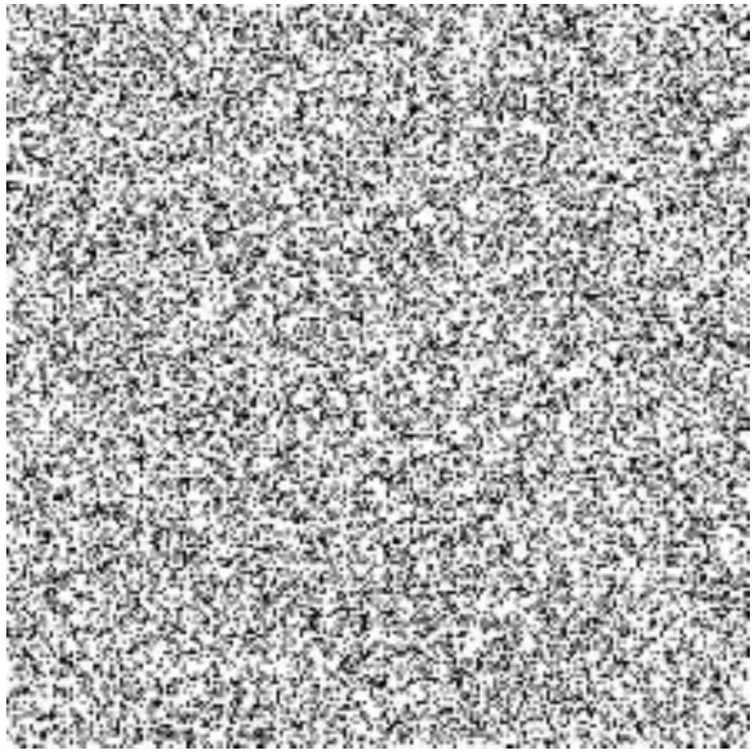
Sometimes motion is the only cue



Slide Credit: S. Lazebnik, but idea of random dot sterogram is due to B. Julesz

Motion and perceptual organization

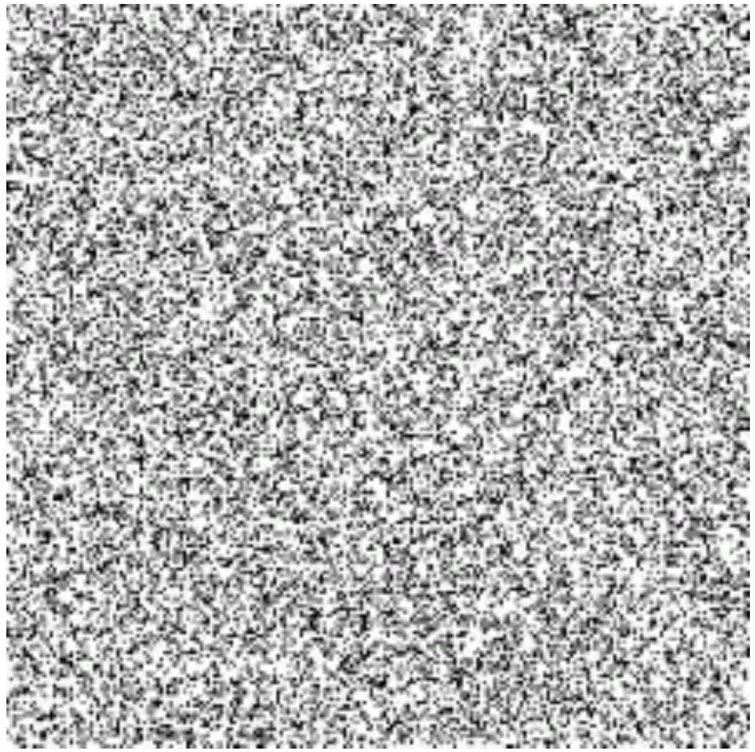
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Motion and perceptual organization

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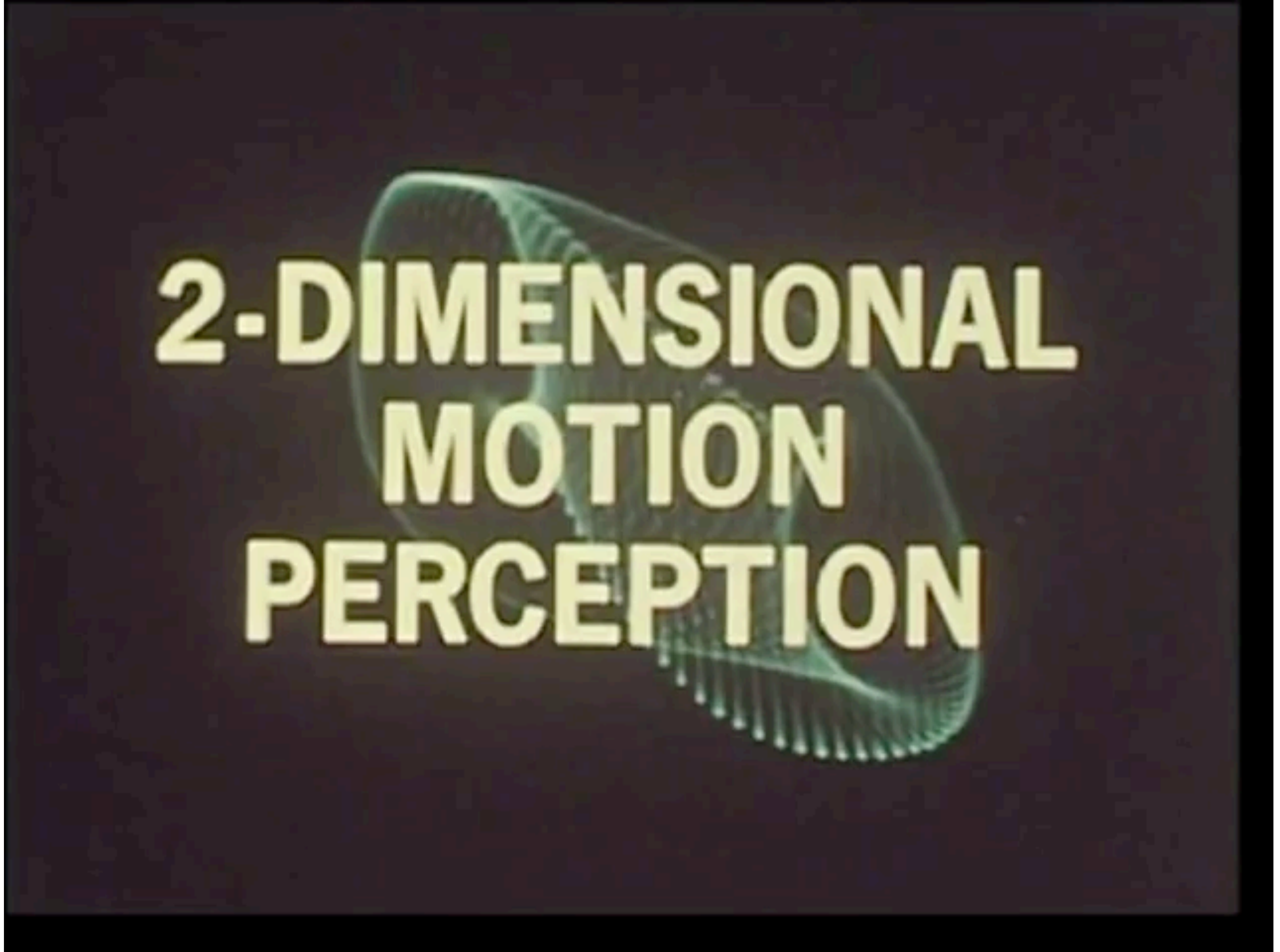


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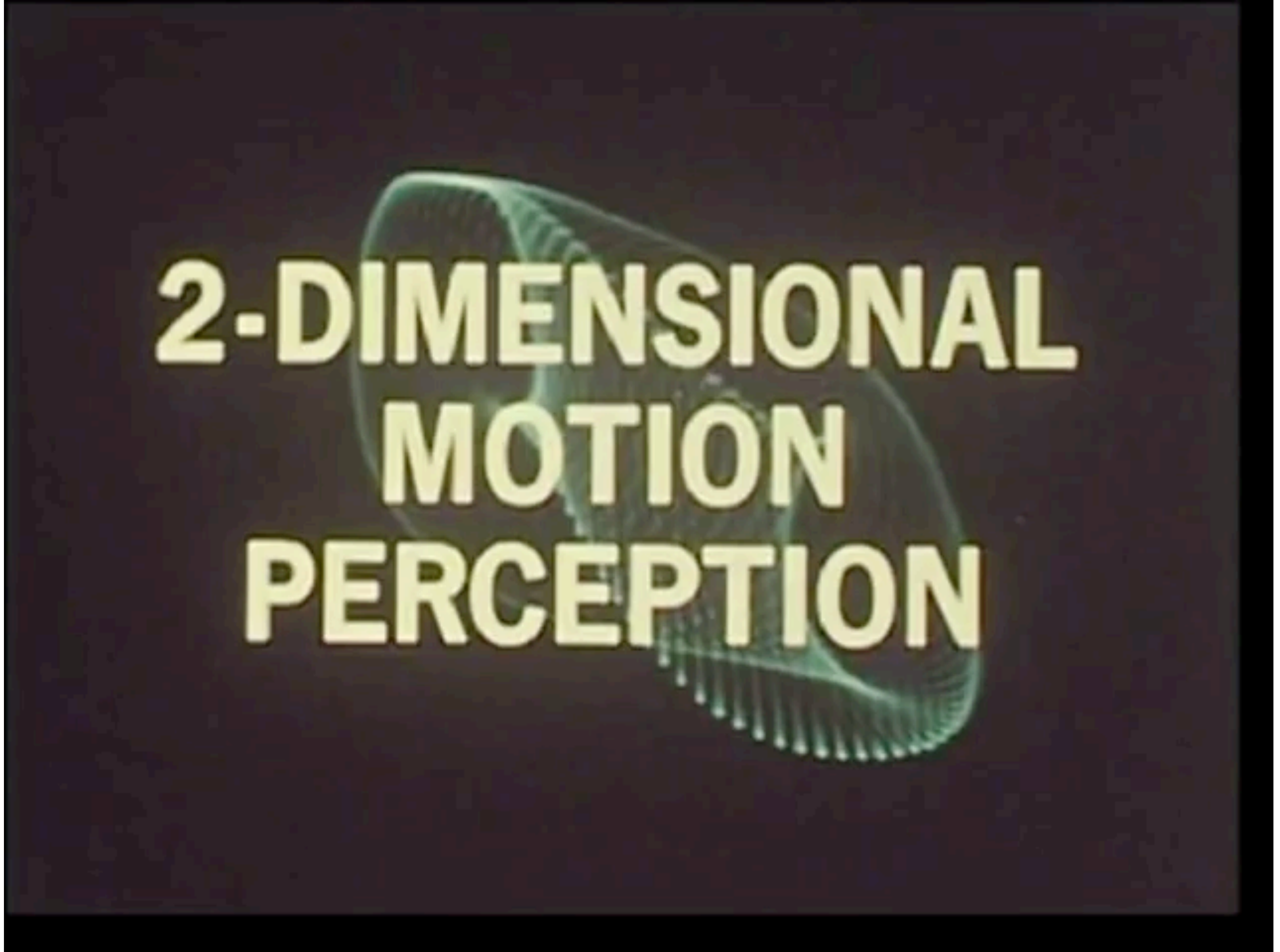
Slide Credit:
C. Rupprecht



Johansson, “Visual perception of biological motion and a model for its analysis.” 1973

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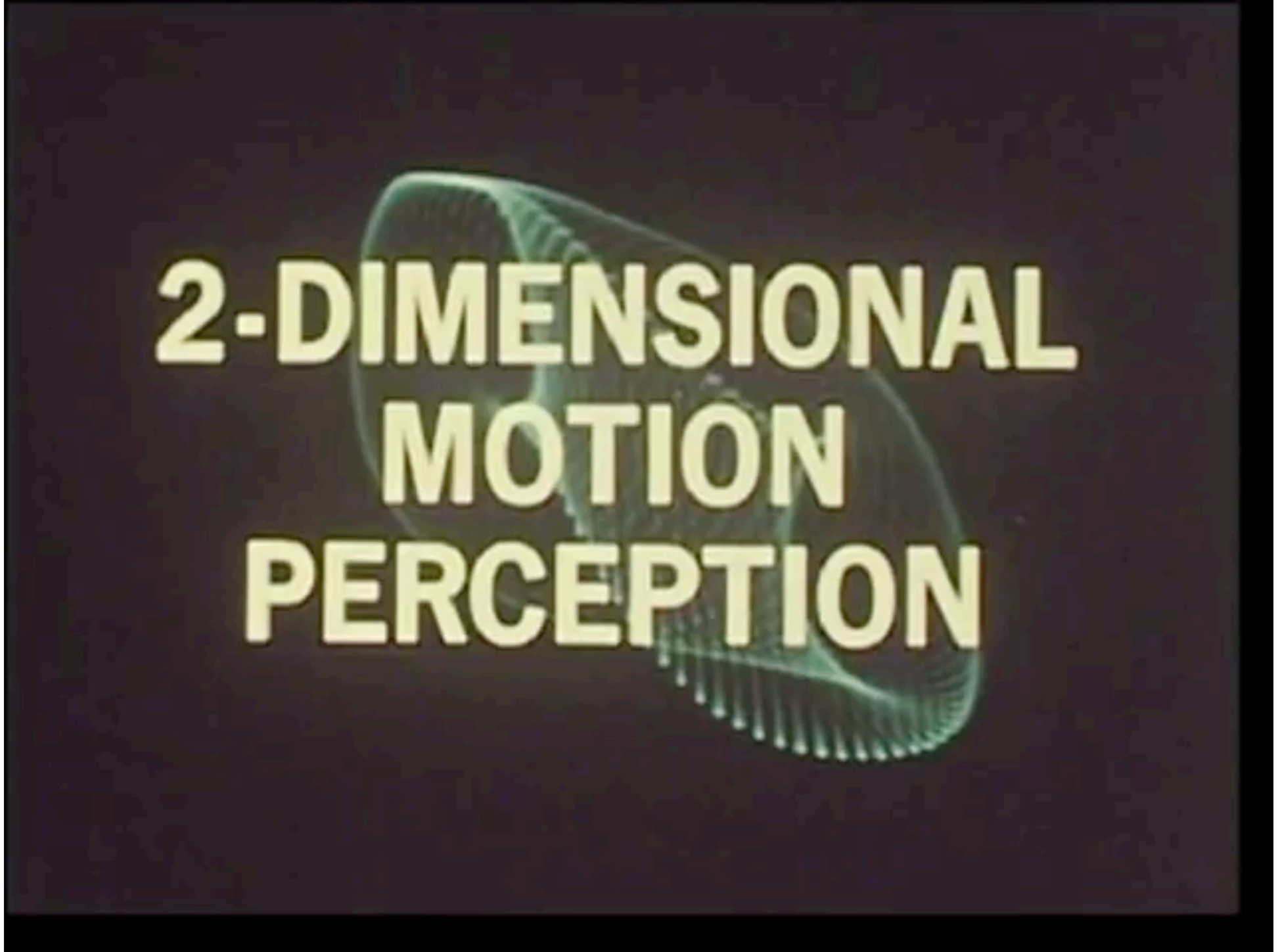
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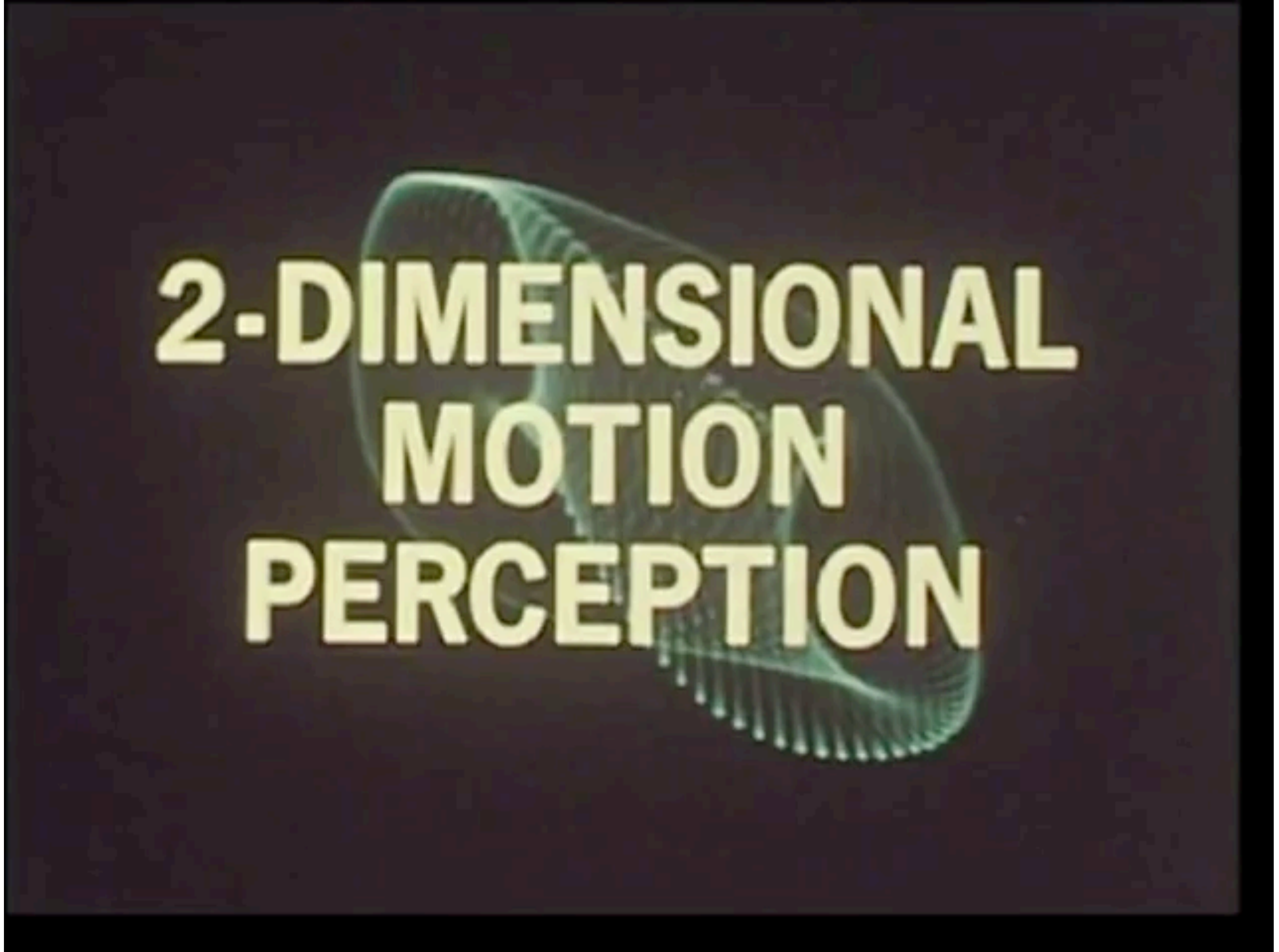
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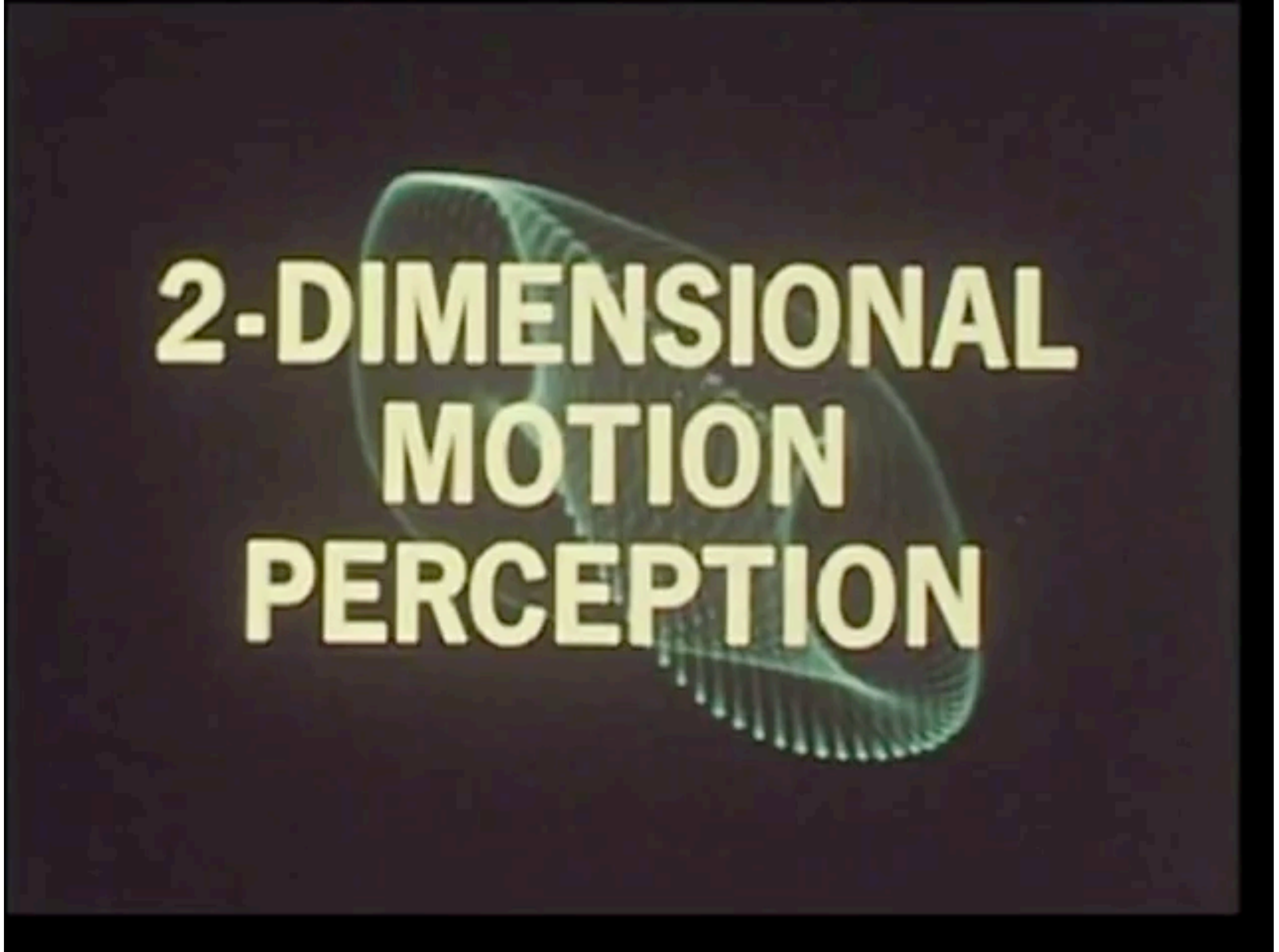
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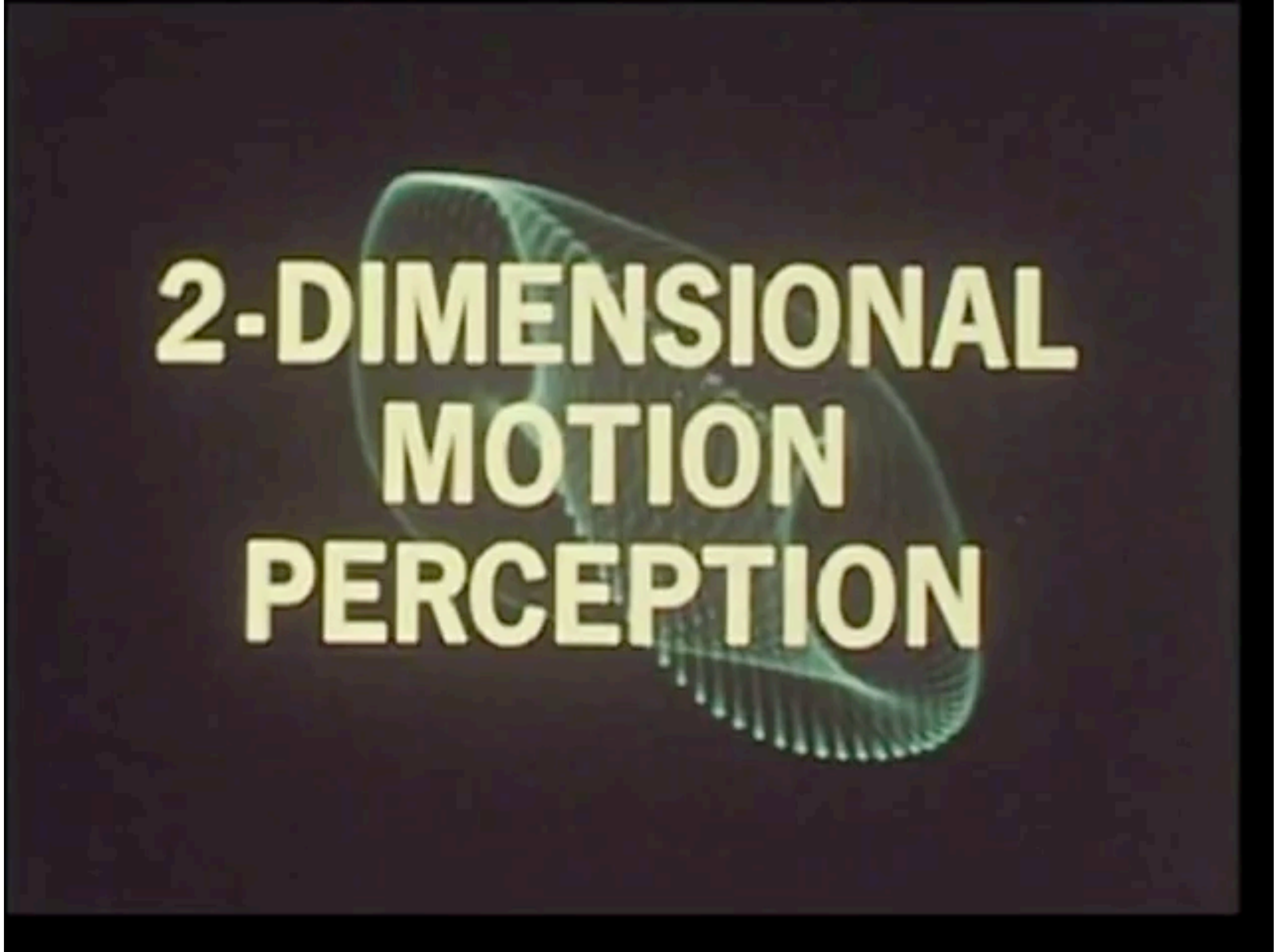
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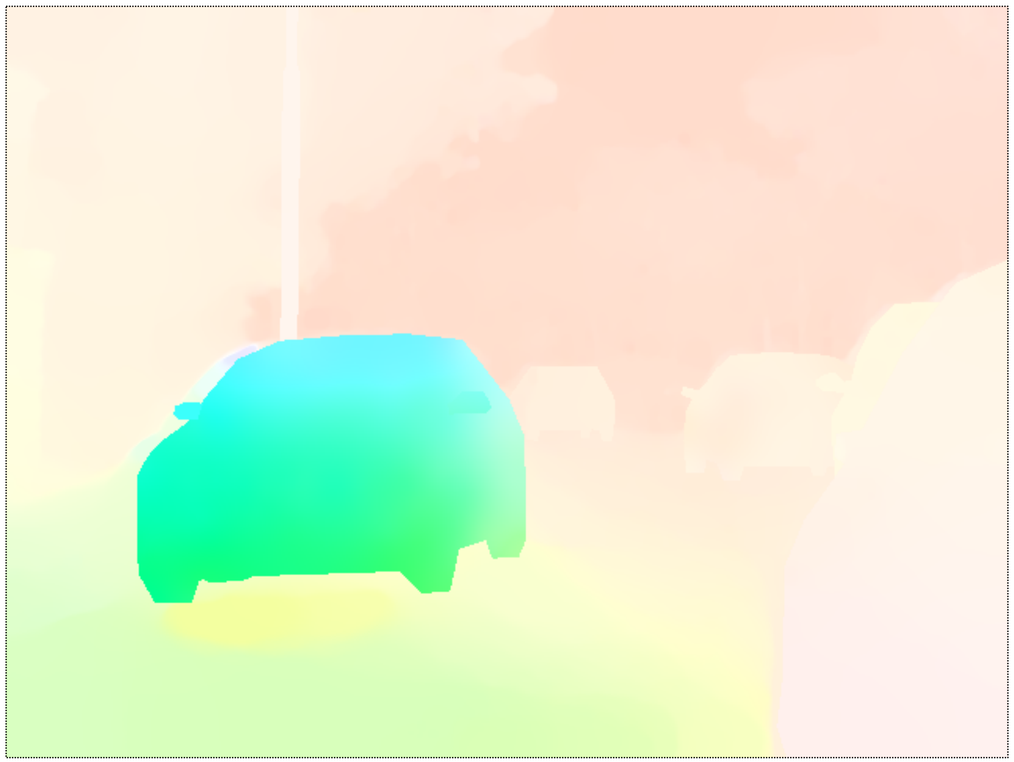
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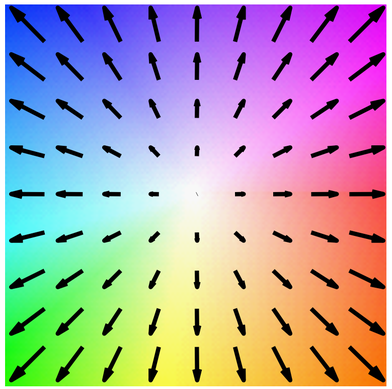
Optical flow: 2D motion of every pixel



Input [Liu *et al.* CVPR'08]



Optical flow (2D motion vector)



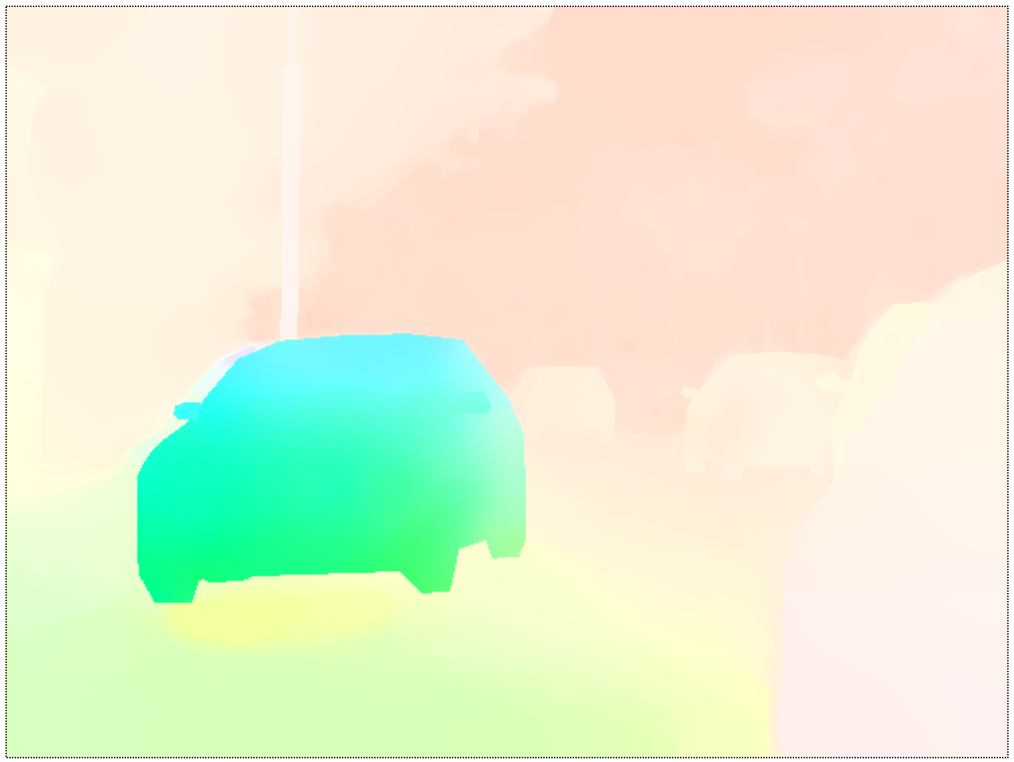
Color key
[Baker *et al.* IJCV'11]

Slide credit: Deqing Sun

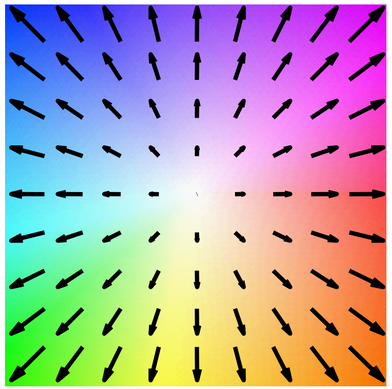
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Color key
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Fundamental assumption: Brightness constancy

[Horn & Schunck AI'81]

Assume a pixel at (x, y, t) with intensity $I(x, y, t)$ has moved by $(\Delta x, \Delta y)$ in space during a timestep Δt.

Color constancy assumption (CCA):

$$I(x, y, t) = I(x + \Delta x, y + \Delta y, t + \Delta t)$$



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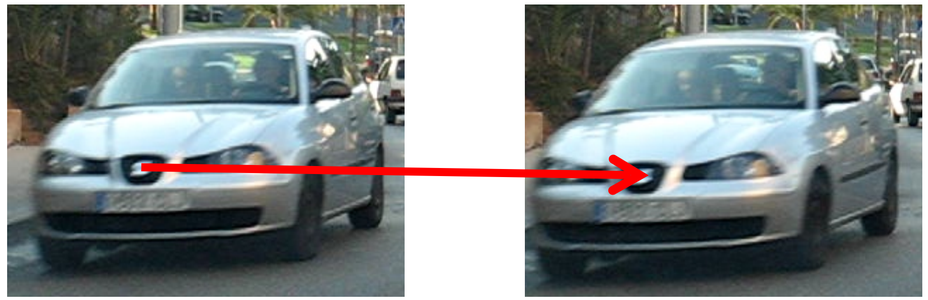
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First image (t)

Second image (t+1)



Berthold Horn

Determining Optical Flow

Berthold K.P. Horn and Brian G. Schunck
Artificial Intelligence Laboratory, Massachusetts Institute of Technology, Cambridge, MA 02139, U.S.A.

ABSTRACT
Optical flow cannot be computed locally, since only one independent measurement is available from the image sequence at a point, while the flow velocity has two components. A second constraint is needed. A method for finding the optical flow pattern is presented which assumes that the apparent velocity of the brightness pattern varies smoothly almost everywhere in the image. An iterative implementation is shown which successfully computes the optical flow for a number of synthetic image sequences. The algorithm is robust in that it can handle image sequences that are quantized rather coarsely in space and time. It is also insensitive to quantization of brightness levels and additive noise. Examples are included where the assumption of smoothness is violated at singular points or along lines in the image.

1. Introduction

Optical flow is the distribution of apparent velocities of movement of brightness patterns in an image. Optical flow can arise from relative motion of objects and the viewer [6, 7]. Consequently, optical flow can give important information about the spatial arrangement of the objects viewed and the rate of change of this arrangement [8]. Discontinuities in the optical flow can help in segmenting images into regions that correspond to different objects [27]. Attempts have been made to perform such segmentation using differences between successive image frames [15, 16, 17, 20, 25]. Several papers address the problem of recovering the motions of objects relative to the viewer from the optical flow [10, 18, 19, 21, 29]. Some recent papers provide a clear exposition of this enterprise [30, 31]. The mathematics can be made rather difficult, by the way, by choosing an inconvenient coordinate system. In some cases information about the shape of an object may also be recovered [3, 18, 19].

These papers begin by assuming that the optical flow has already been determined. Although some reference has been made to schemes for comput-

Artificial Intelligence **17** (1981) 185–203
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Horn & Schunck Optical Flow





Horn & Schunck Optical Flow

Taylor expansion:

$$I(x + \Delta x, y + \Delta y, t + \Delta t) \approx I(x, y, t) + \frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t$$





Horn & Schunck Optical Flow

With CCA:

$$\frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t = 0 \quad \text{or} \quad \frac{\partial I}{\partial x}\frac{\Delta x}{\Delta t} + \frac{\partial I}{\partial y}\frac{\Delta y}{\Delta t} + \frac{\partial I}{\partial t} = 0$$





Horn & Schunck Optical Flow





Using $\nabla I = \left[\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right]^T$ and $\mu = \left[\frac{\Delta x}{\Delta t}, \frac{\Delta y}{\Delta t}\right]^T$

yields the **motion constraint equation:**

$$\nabla \mathbf{I}\mu = -\frac{\delta I}{\delta t}$$

Thinking About Horn & Schunck Optical Flow

$$\nabla \mathbf{I}\mu = -\frac{\delta I}{\delta t}$$

To use for optical flow estimation, put into a loss function:

$$E = \min_{\mu} \left[(\nabla^T \mathbf{I}_1 \mu - (\mathbf{I}_2 - \mathbf{I}_1))^2 \right]$$

It’s convex (can be solved via gradient descent or closed-form)!

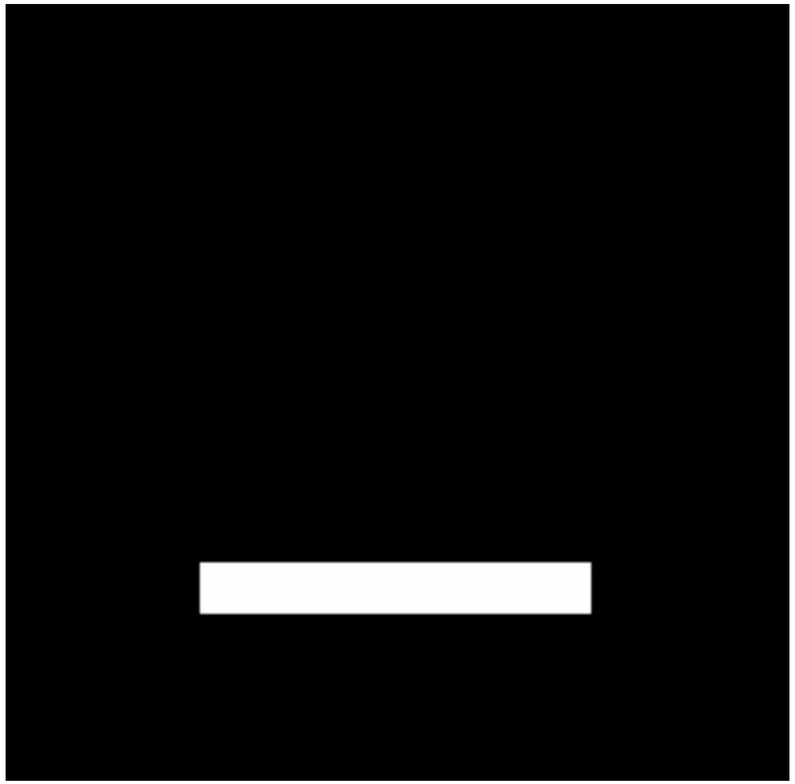
Thinking About Horn & Schunck Optical Flow

$$\nabla \mathbf{I}\mu = -\frac{\delta I}{\delta t}$$

Remarkable: Only the *image gradient* matters for time evolution!
Why? Think about it.

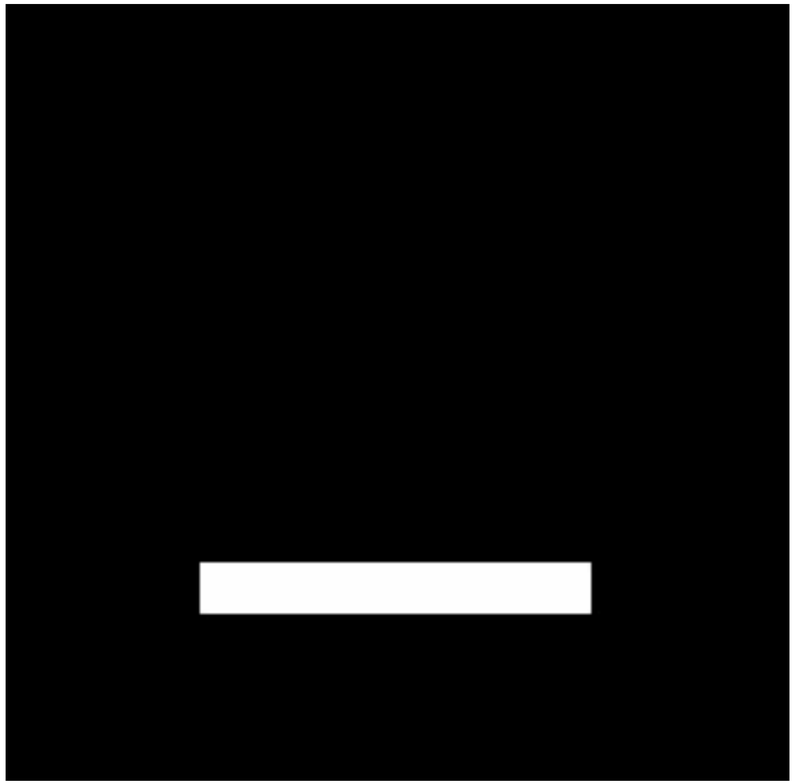
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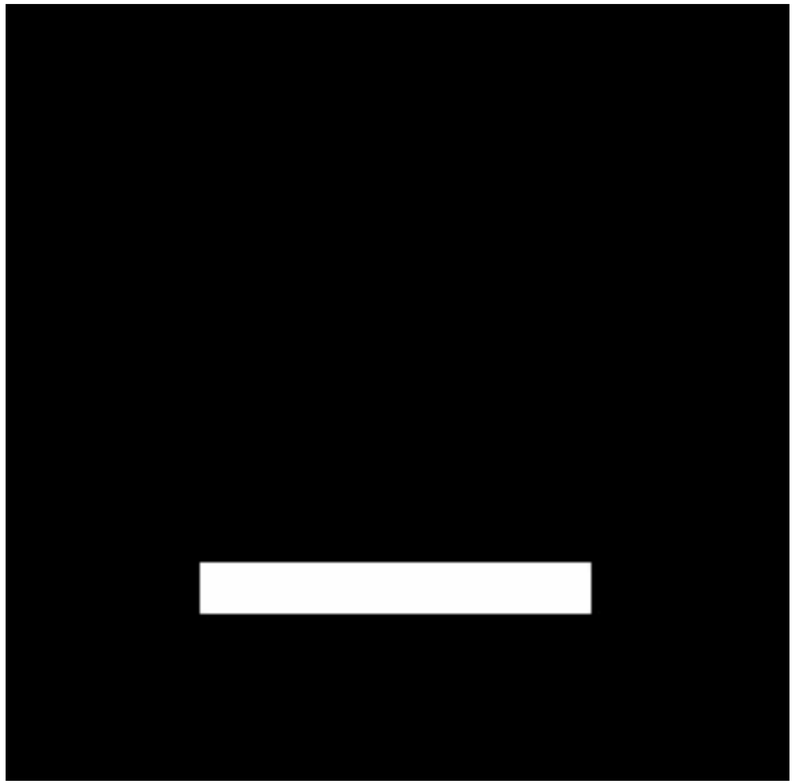
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Optical Flow – The Beginnings

[Horn & Schunck AI'81]



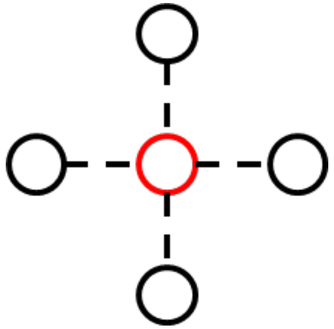
Raw estimate

Optical Flow – The Beginnings

[Horn & Schunck AI'81]



Raw estimate



Prior term (Smoothness)

Optimization/energy minimization

[Horn & Schunck AI'81]



Data term (Constancy)

Prior term (Smoothness)

$$E = \min_{\mu} \left[(\nabla^T \mathbf{I}_1 \mu - (\mathbf{I}_2 - \mathbf{I}_1))^2 + \alpha(|\nabla \mu_x|^2 + |\nabla \mu_y|^2) \right]$$

Optical Flow – The Beginnings

[Horn & Schunck AI'81]



Raw estimate

[Horn & Schunck AI'81]



Smoothed estimate

Horn & Schunck on a more recent scene





Horn & Schunck on a more recent scene





Thinking About Horn & Schunck Optical Flow

$$\nabla \mathbf{I}\mu = -\frac{\delta I}{\delta t}$$

Some strong assumptions:
Was derived assuming *infinitesimal translation* $(\Delta x, \Delta y)$*!*
Get different equations for infinitesimal rotation, homography, scale…

From the gradient perspective, you can see that motion
is really assumed to be *small.*

Matching-based motion estimation

Generally: Energy to measure similarity between a pixel in image 1 with pixels in image 2:

$$\min_{\mathbf{w_p}} \left(I_t(\mathbf{p}) - I_{t+1}\left(\mathbf{p} + \mathbf{w_p}\right)\right)^2$$



Image 1



Image 2

Matching-based motion estimation

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Image 1

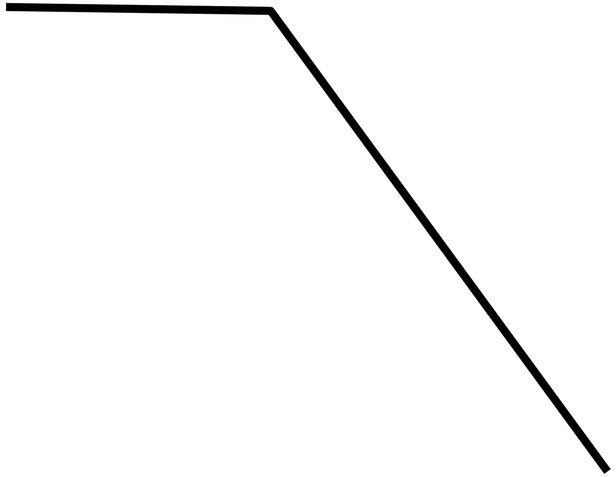


Image 2

Comparing pixel colors directly

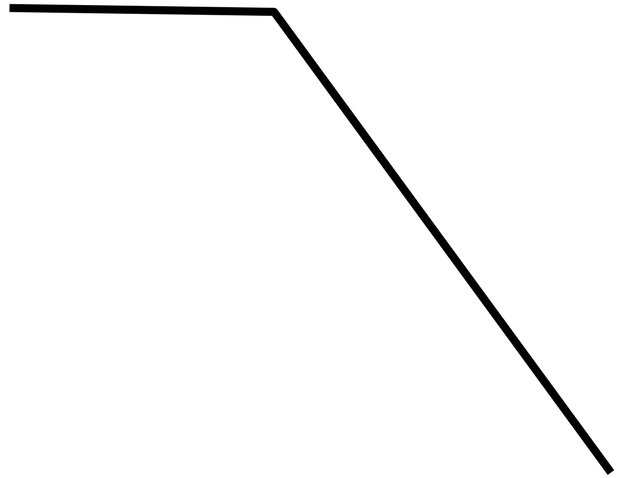


Estimating Motion in Direction of Constant Brightness: The Aperture Problem



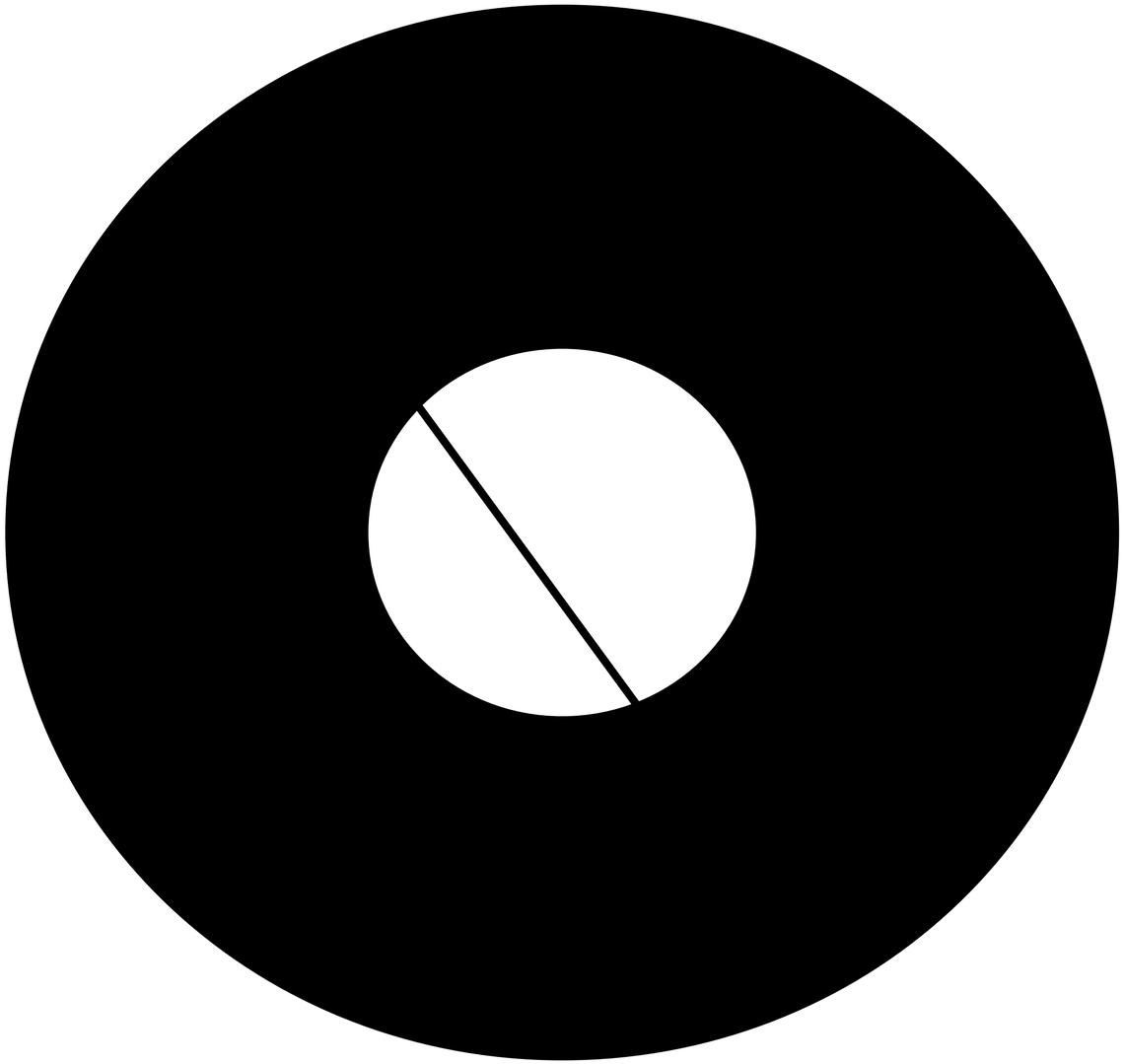
Slide Credit: S. Lazebnik

Estimating Motion in Direction of Constant Brightness: The Aperture Problem



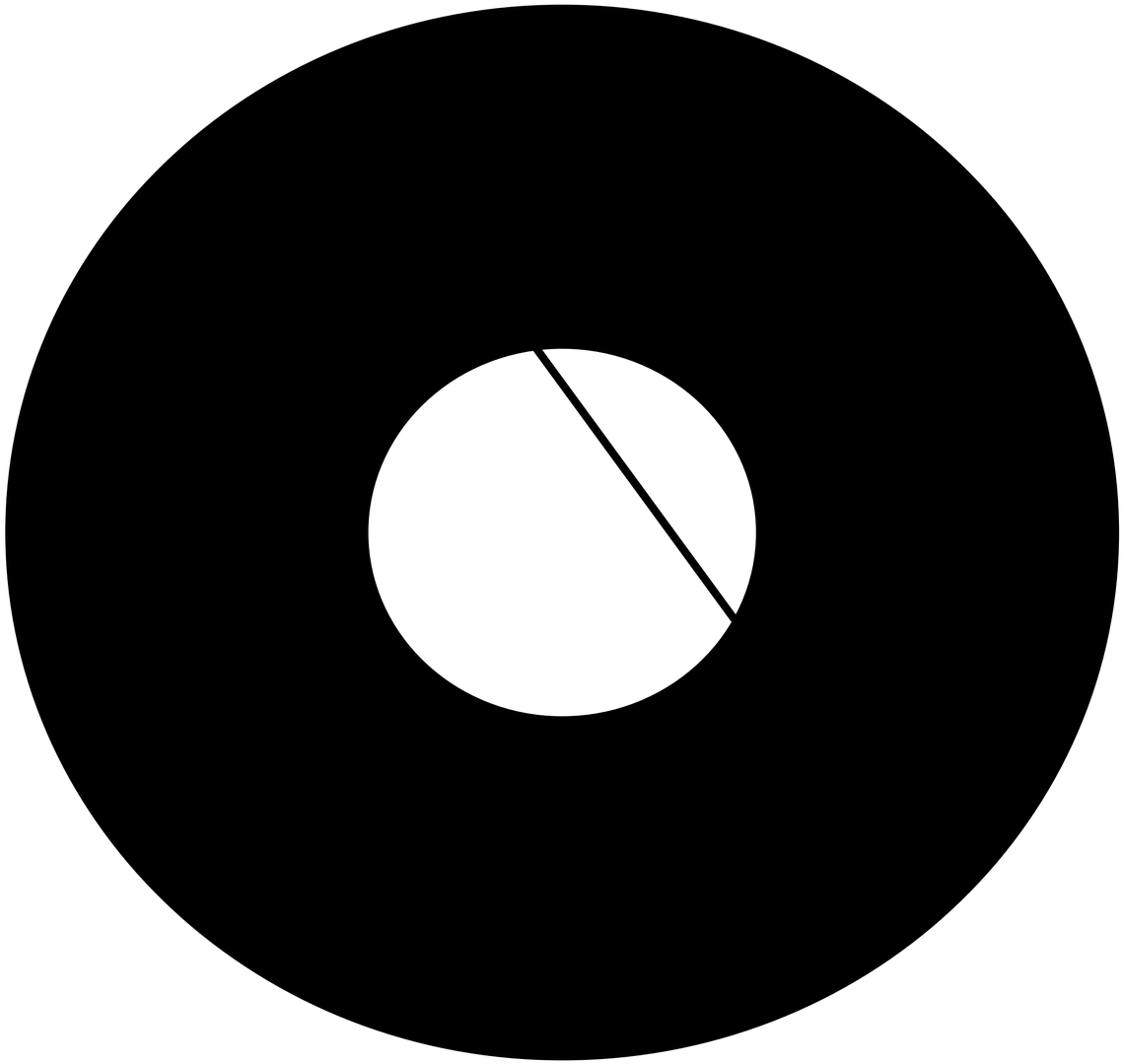
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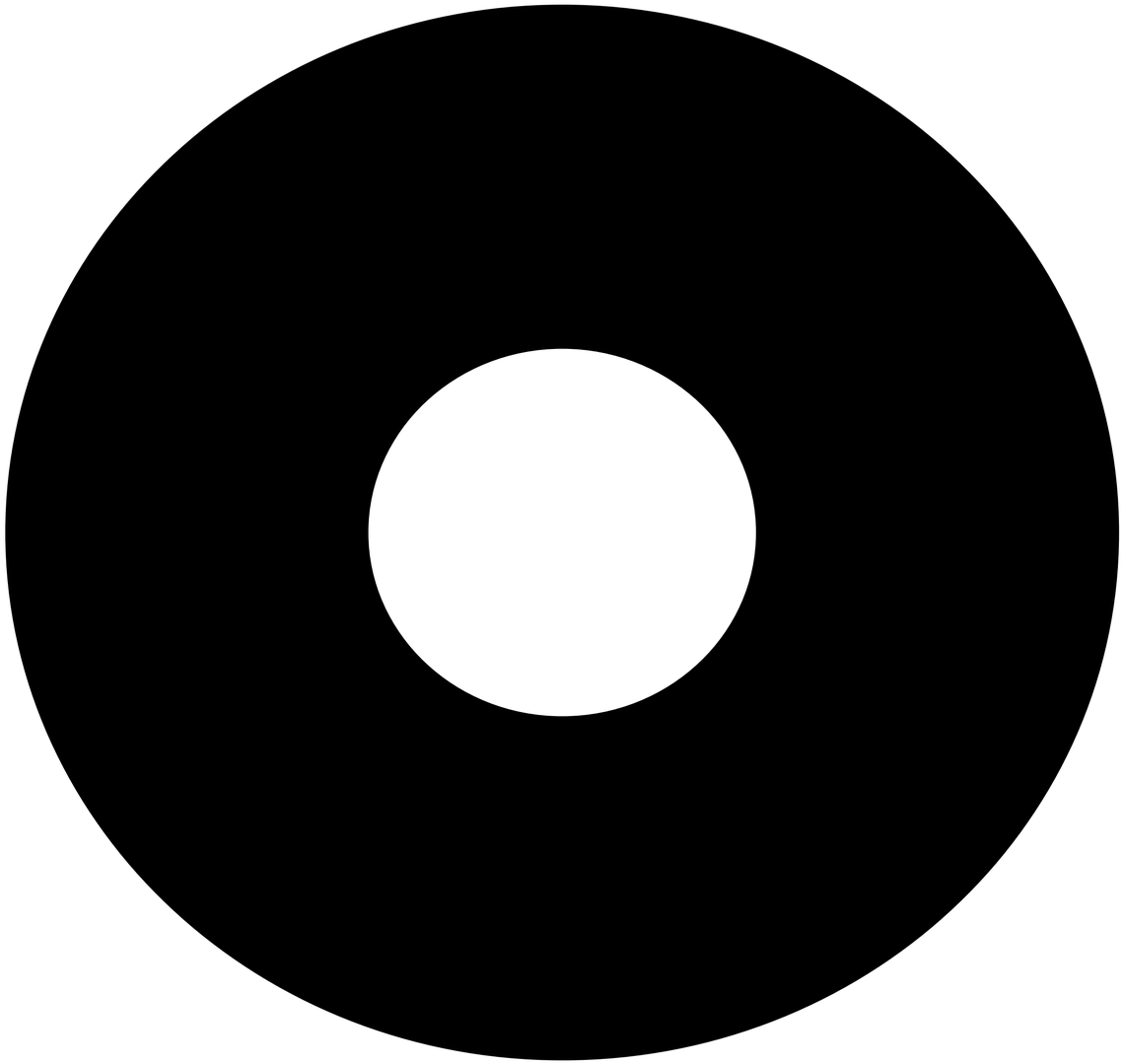
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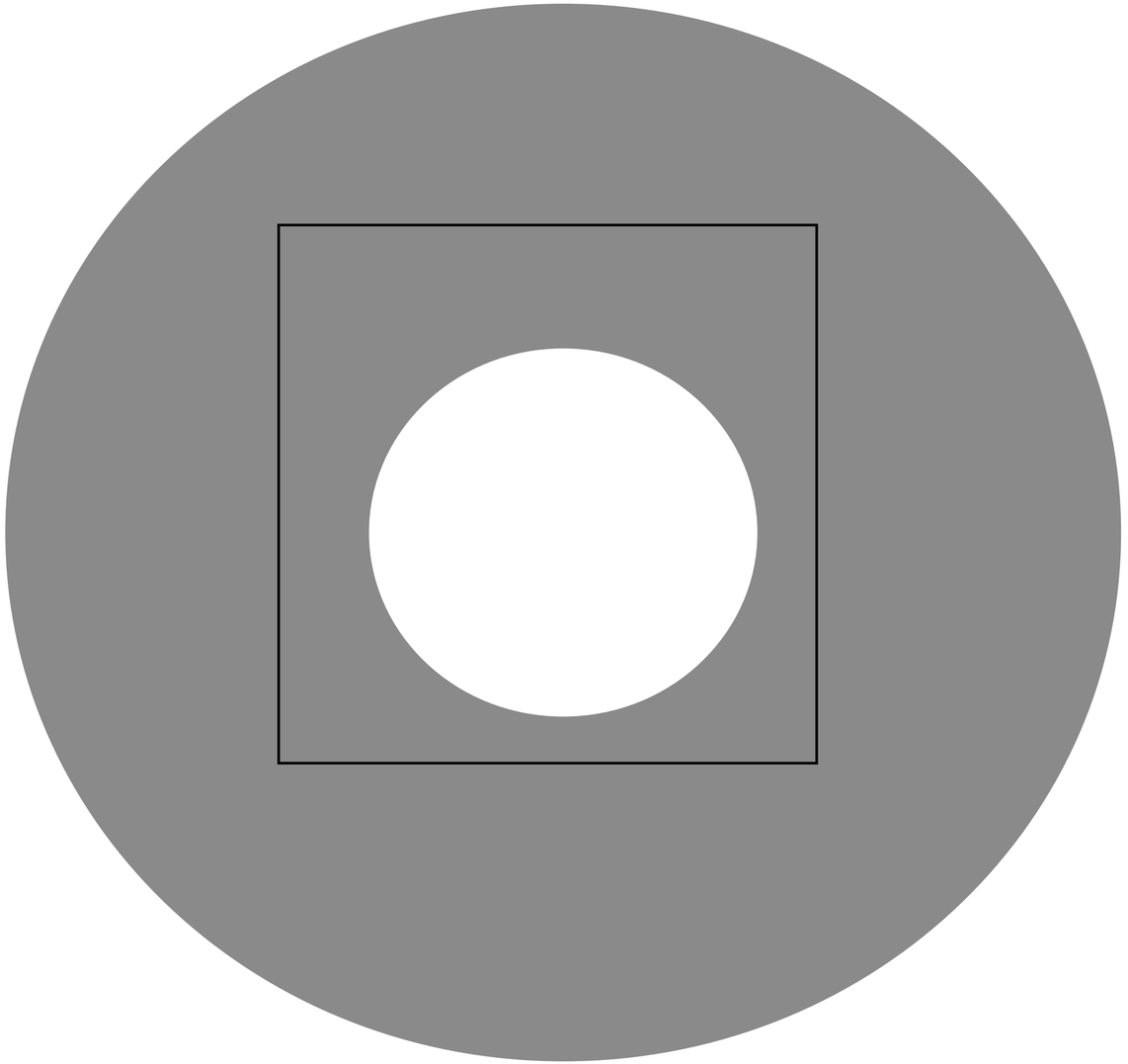
Slide Credit: S. Lazebnik

Other invisible flow



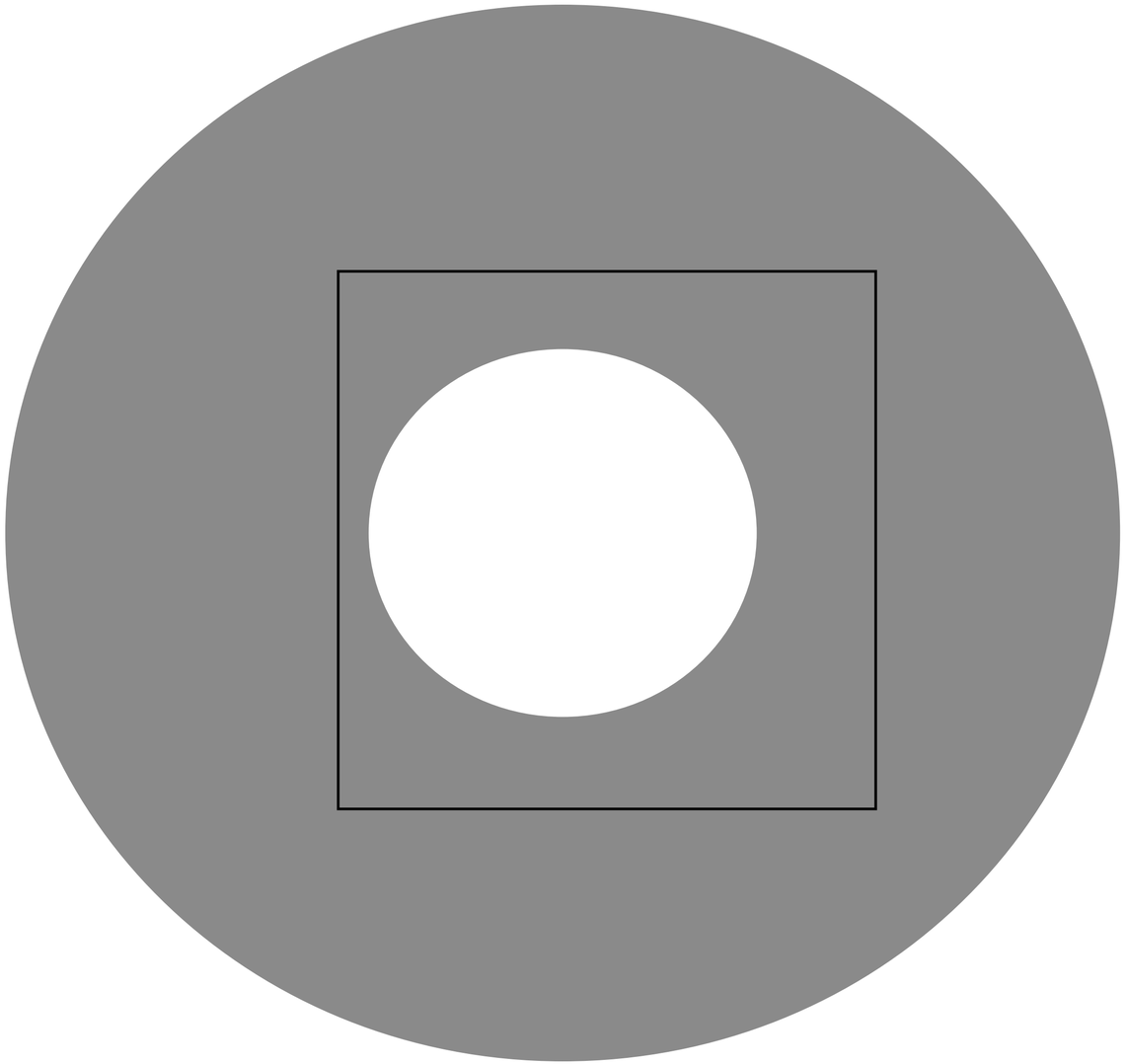
Slide credit: D Fouhey & J Johnson

Other invisible flow



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Other invisible flow



Slide credit: D Fouhey & J Johnson

What do you perceive?



What do you perceive?



Matching-based motion estimation

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$$\min_{\mathbf{w_p}} \left(I_t(\mathbf{p}) - I_{t+1}\left(\mathbf{p} + \mathbf{w_p}\right)\right)^2$$



Image 1



Image 2

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Image 1



Image 2

Resolving ambiguities: Lucas-Kanade

Insight: Pixels in the same patch generally share the same motion

$$\min_{\mathbf{w_p}} \sum_{\mathbf{q} \in N_p} \left(I_t(\mathbf{q}) - I_{t+1}\left(\mathbf{q} + \mathbf{w_p}\right) \right)^2$$



Image 1



Image 2

Resolving ambiguities: Lucas-Kanade

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Image 2

Resolving ambiguities: Lucas-Kanade

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Image 1



Image 2

Cost / Correspondence Volumes

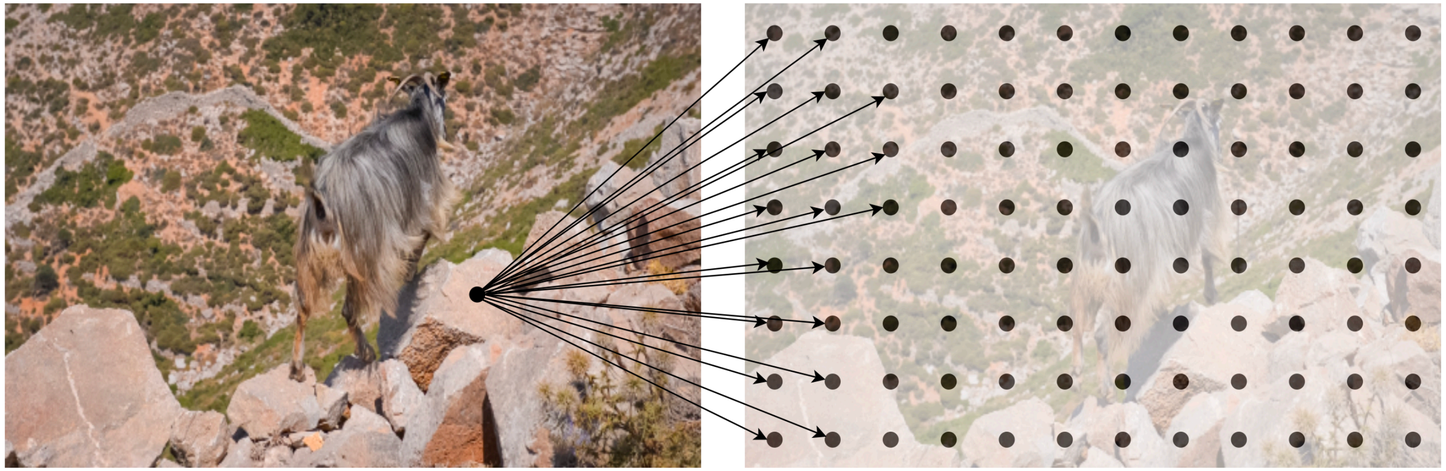
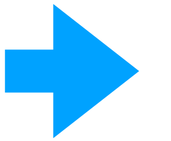
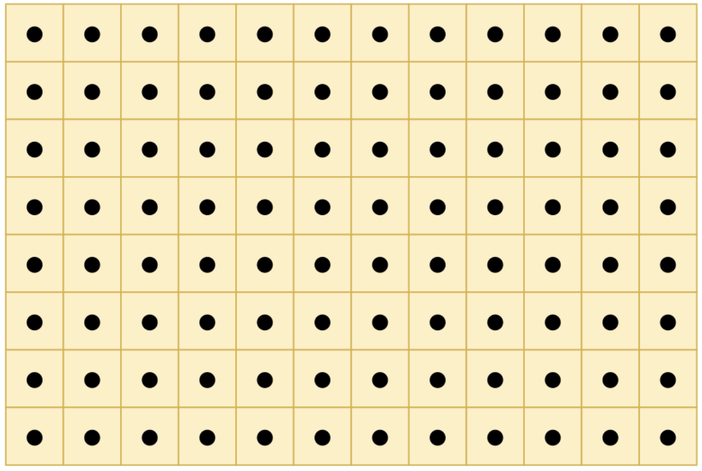


Image 1

Image 2

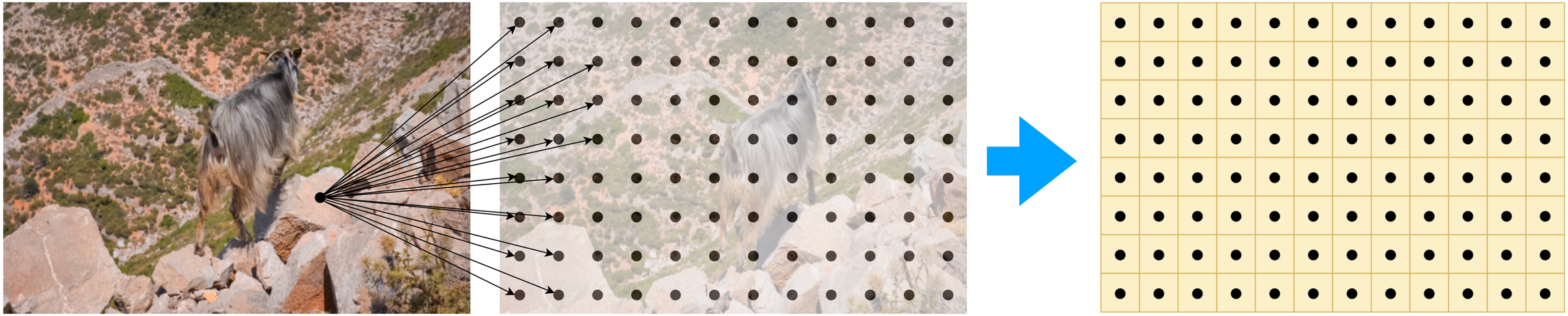




$\mathbf{C}^1 \in H \times W \times H \times W$

Image Courtesy: RAFT. *Teed et. al.*

Cost / Correspondence Volumes



Idea: Correlate every pixel / patch in image 1 with every pixel in image 2, yielding a 4D **correlation volume.**

Image Courtesy: RAFT. *Teed et. al.*

Similarity between patches (cost volume)

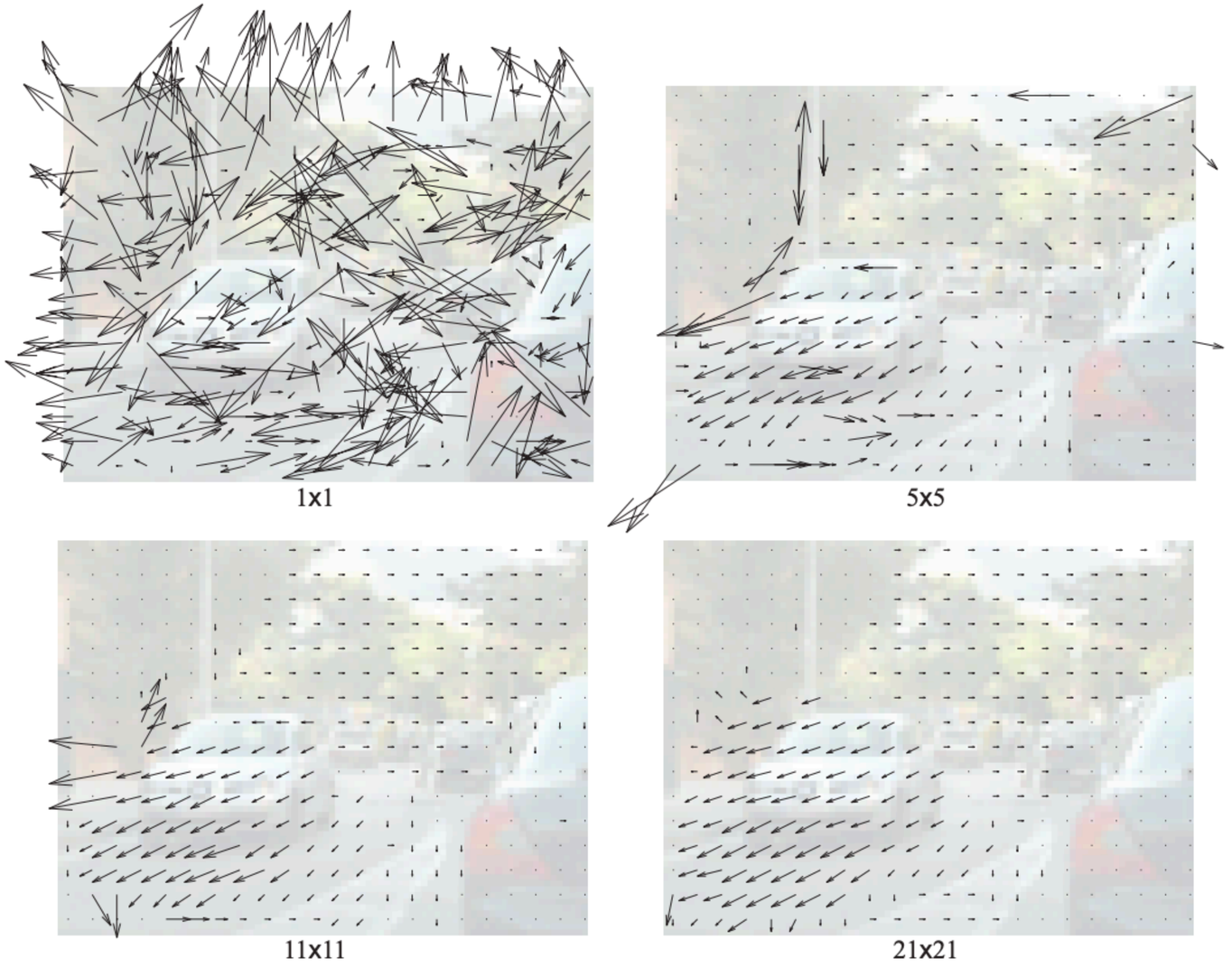


Image 1



Cost volume (darker, more similar)

Effect of patch size



Issue: Brute force is too expensive

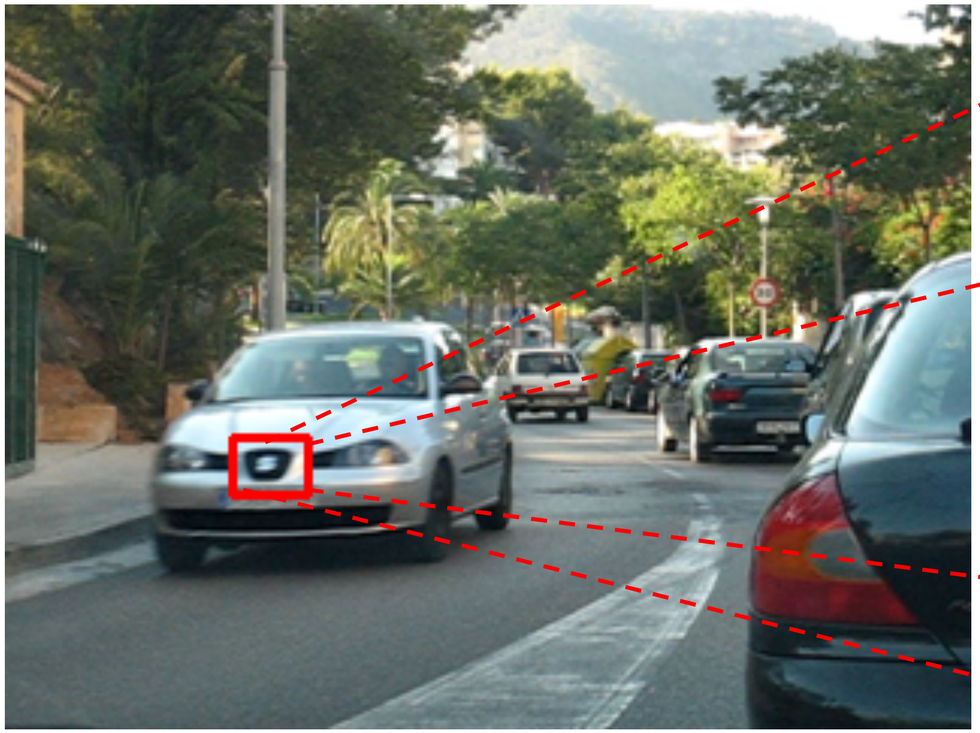


Image 1

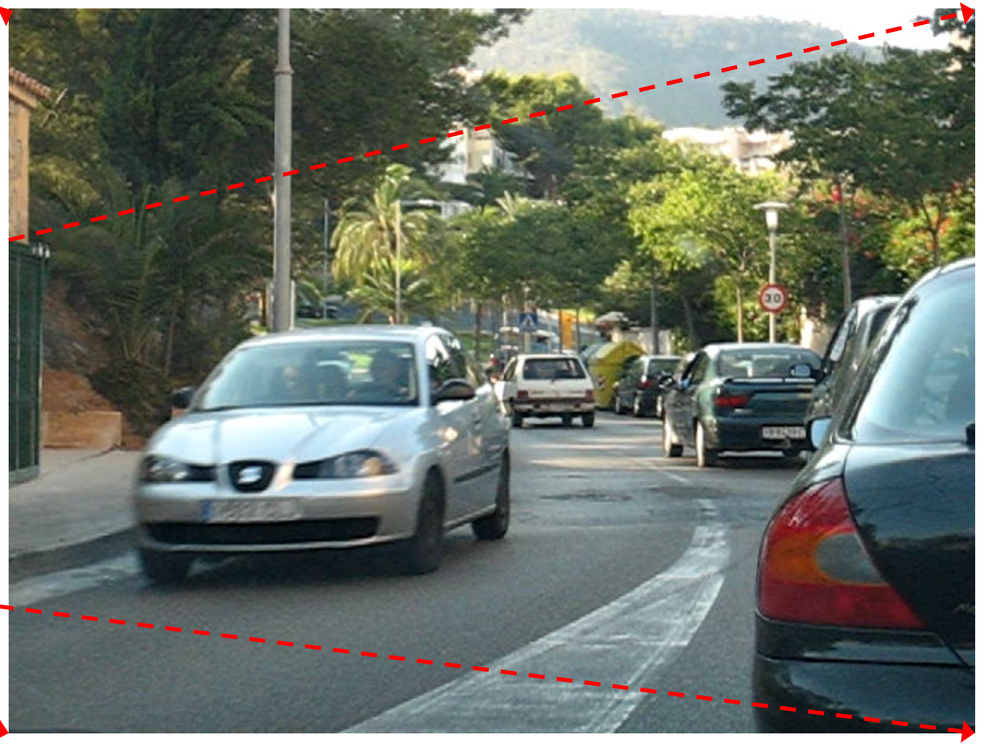
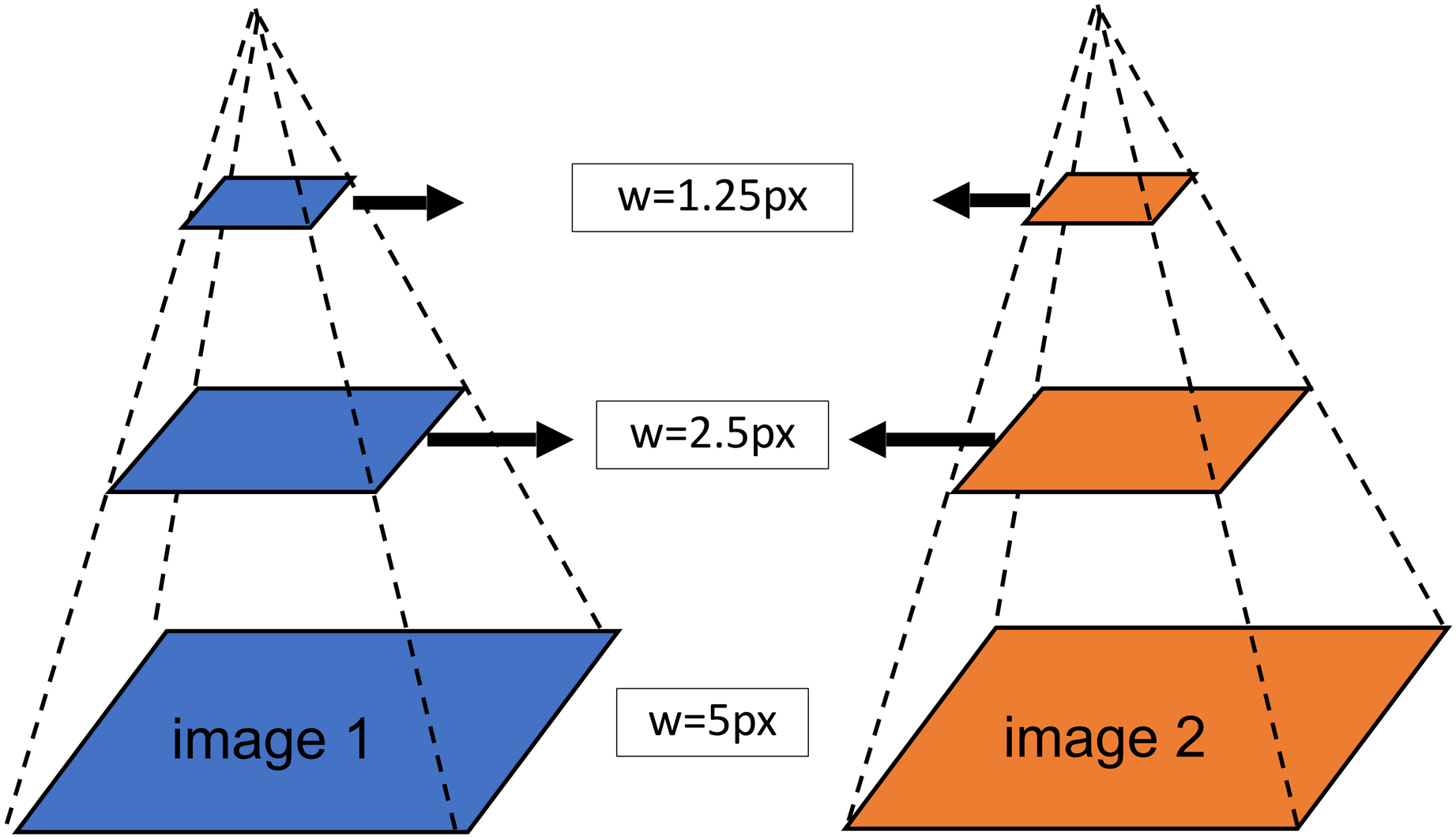


Image 2

Coarse-to-fine iterative estimation



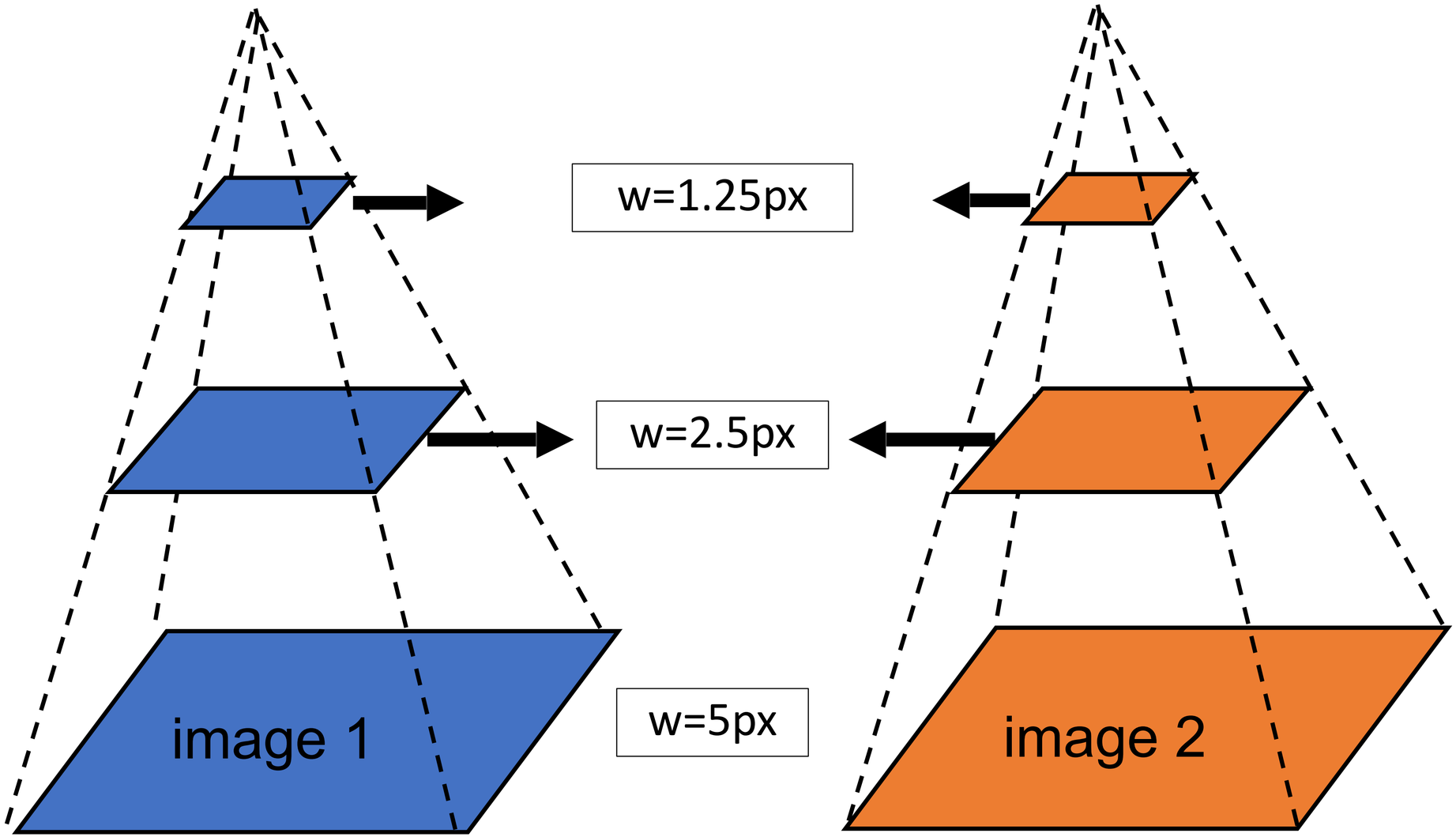






Slide credit: S. Lazebnik

Coarse-to-fine iterative estimation



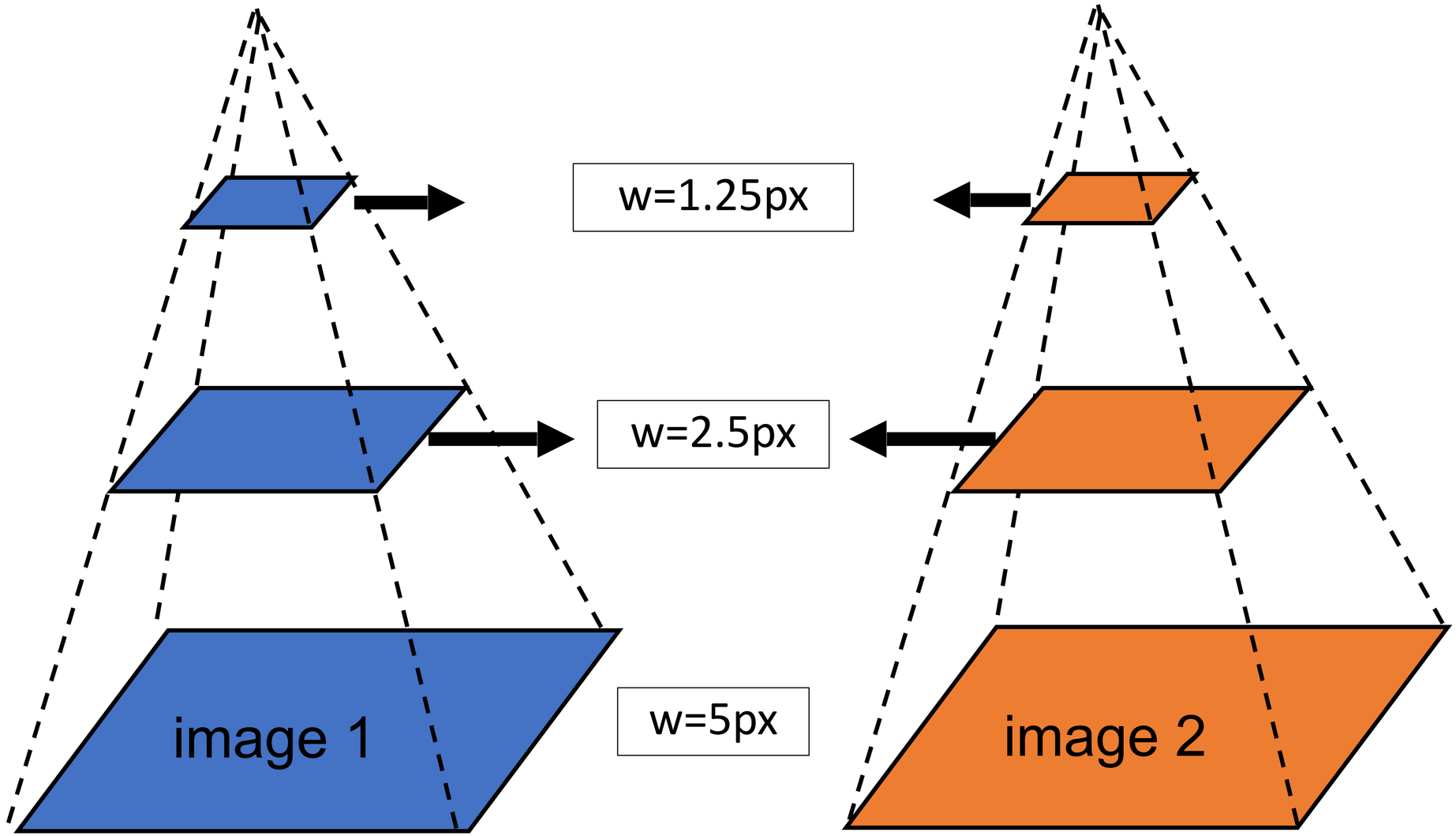






Slide credit: S. Lazebnik

Coarse-to-fine iterative estimation





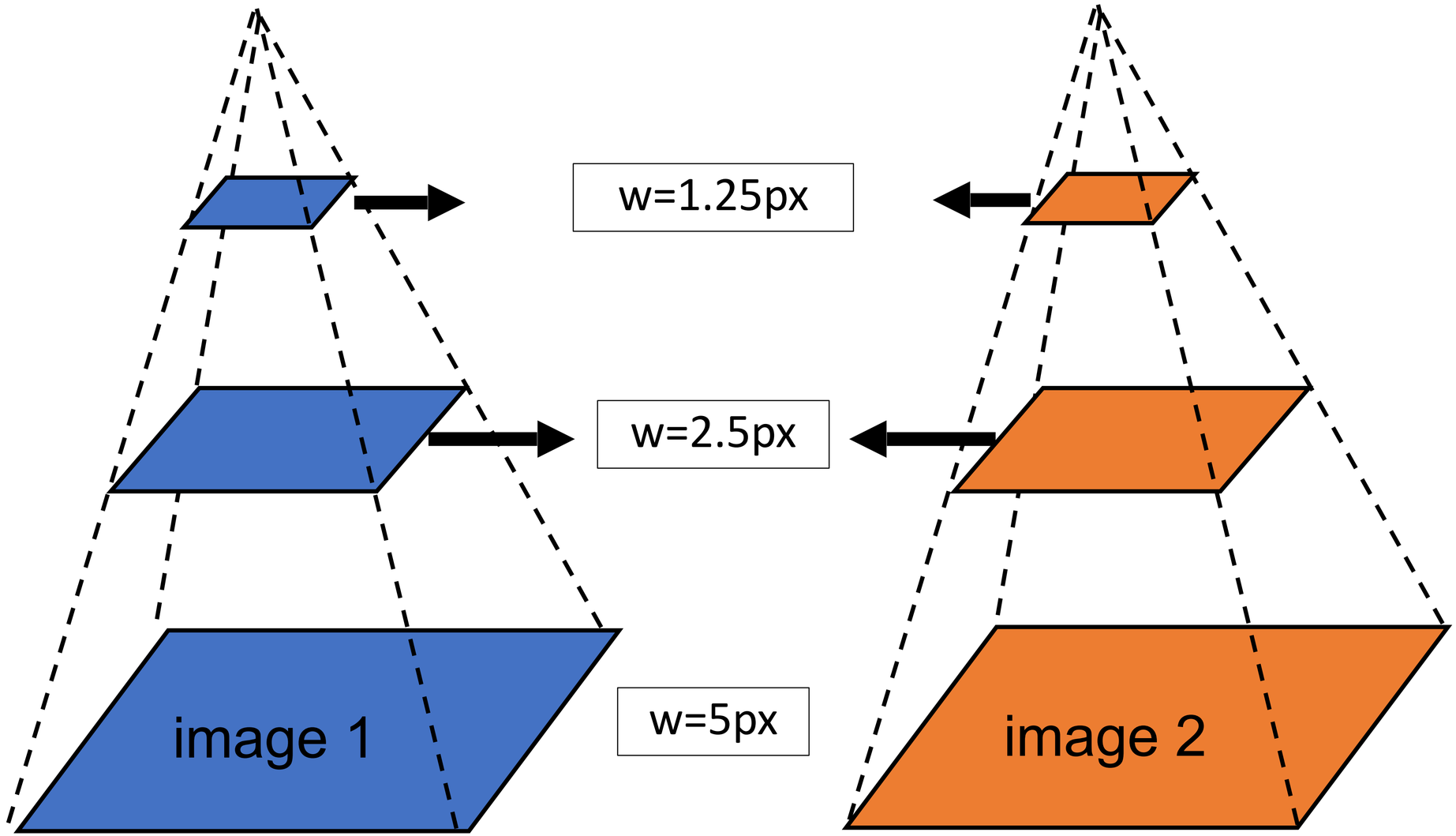




Start from top or bottom?

Slide credit: S. Lazebnik

Coarse-to-fine iterative estimation



How to use estimates from the upper level?

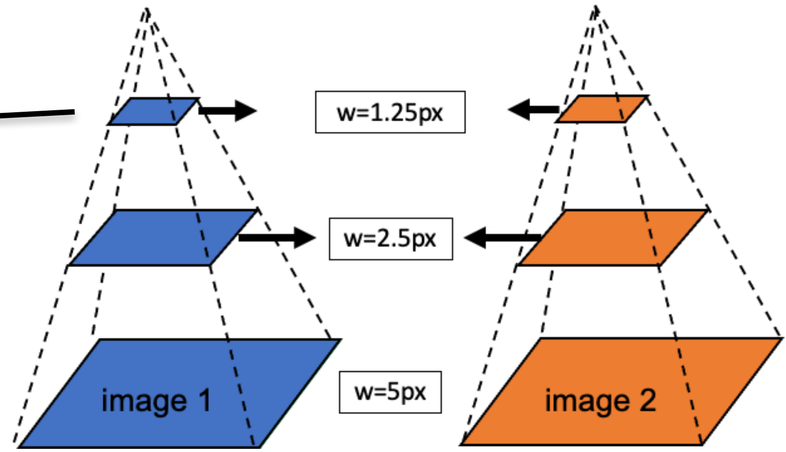
Slide credit: S. Lazebnik

Coarse-to-fine iterative estimation

Current estimate

$$I_{t+1}\left(\mathbf{q}+\mathbf{w_p}\right) = I_{t+1}\left(\mathbf{q}+\mathbf{w_p}^{k}+\delta\mathbf{w_p}\right) = \mathbf{I_w}(\mathbf{q}+\delta\mathbf{w_p})$$

Small increment

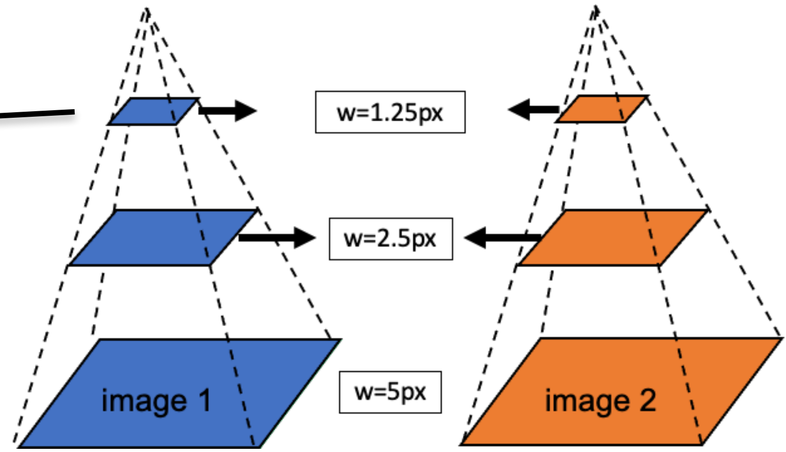


Coarse-to-fine iterative estimation

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Small increment



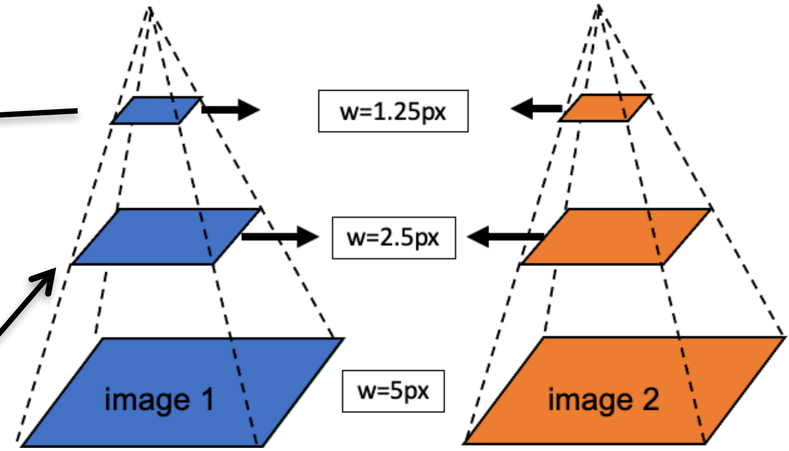
Warped image:

Coarse-to-fine iterative estimation

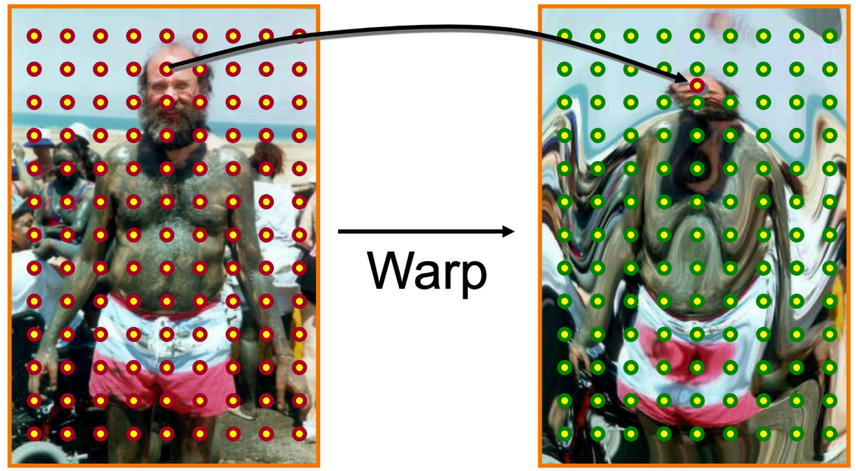
Current estimate

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Small increment



Warped image: $I_{\mathrm{w}}(\mathbf{q})=I_{t+1}\left(\mathbf{q}+\mathbf{w}_{\mathbf{p}}^{k}\right)$



Source image

Destination image

Warping operation

$$I_{\mathrm{w}}(\mathbf{q}) = I_{t+1}\left(\mathbf{q} + \mathbf{w}_{\mathbf{p}}^{k}\right)$$



Input images *t* and *t*+1



Image *t* and warped image

Warping operation

$$I_{\mathrm{w}}(\mathbf{q}) = I_{t+1}\left(\mathbf{q} + \mathbf{w}_{\mathbf{p}}^{k}\right)$$



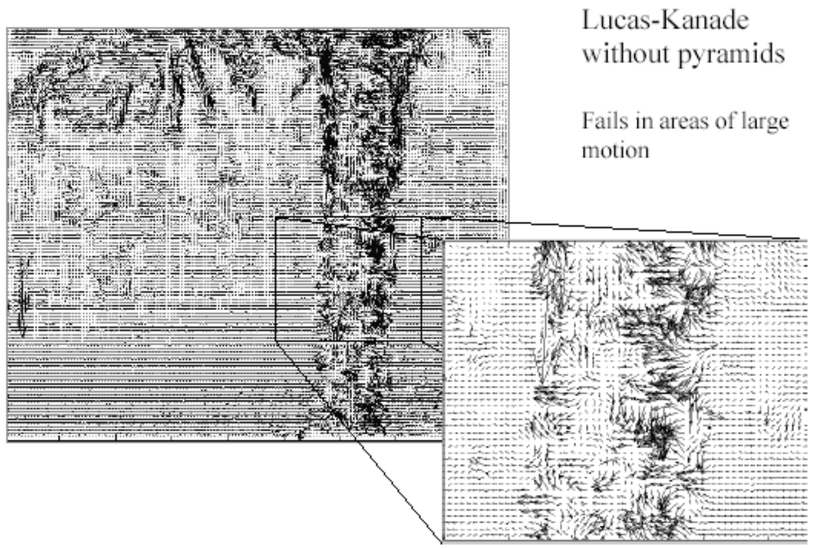
Input images *t* and *t*+1

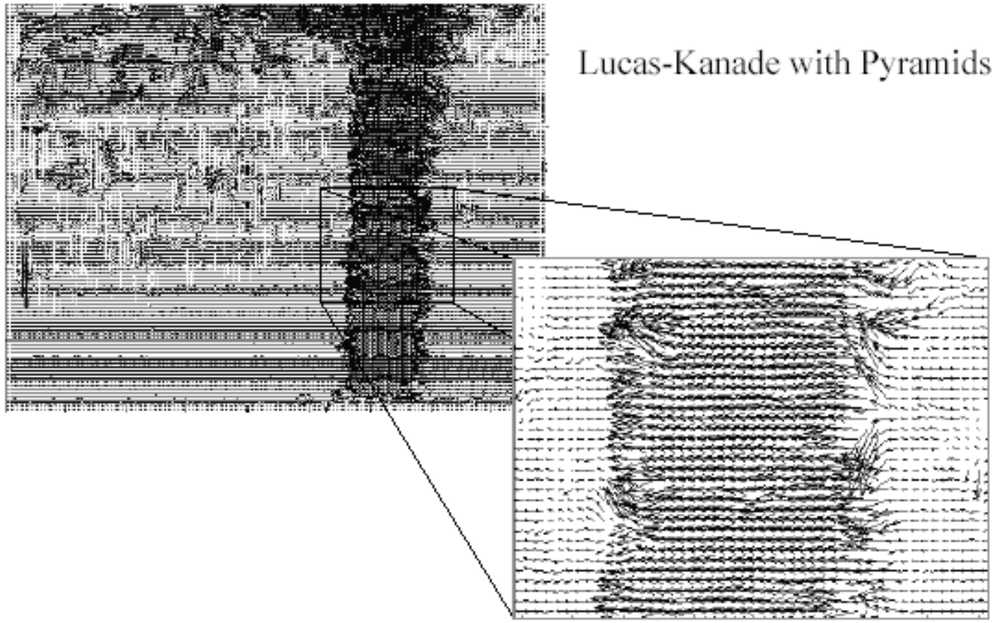


Image *t* and warped image

Optical Flow Results



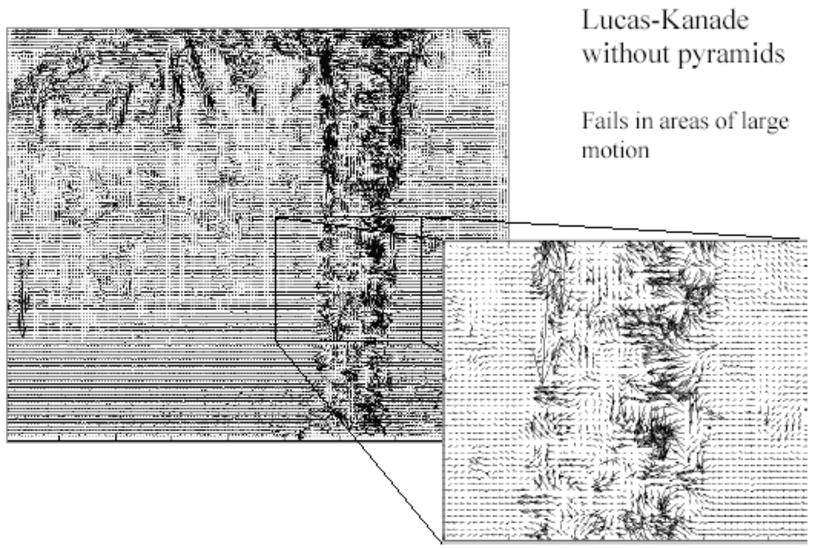


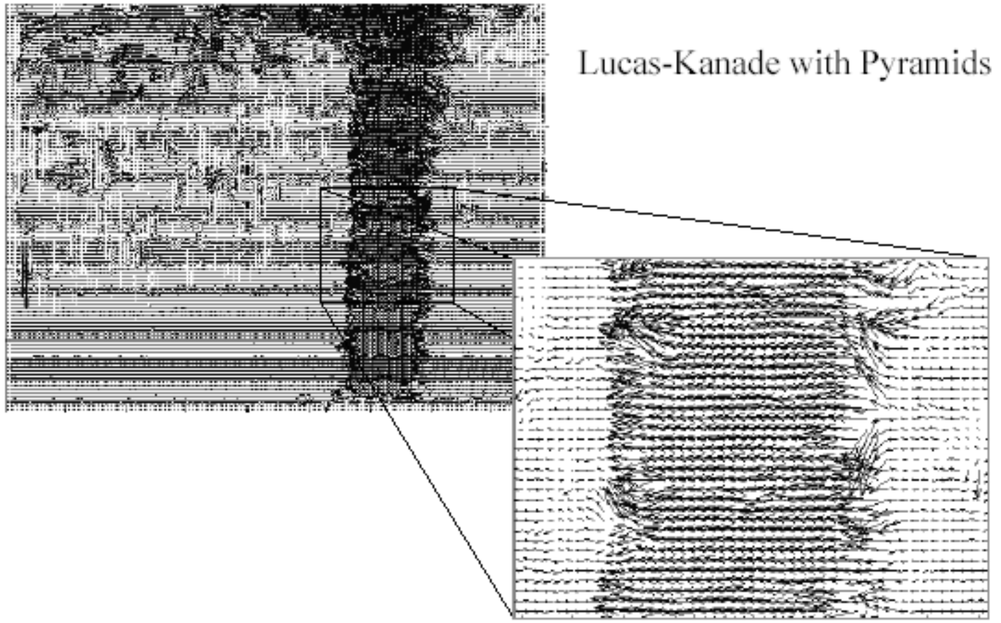


Slide credit: S. Lazebnik

Optical Flow Results



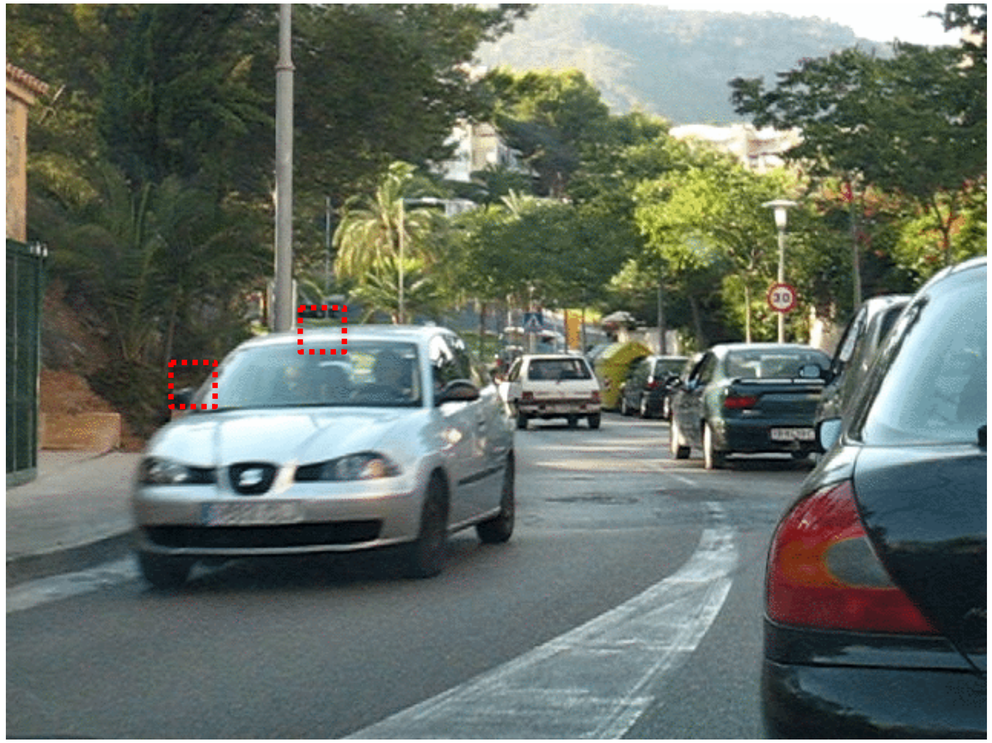


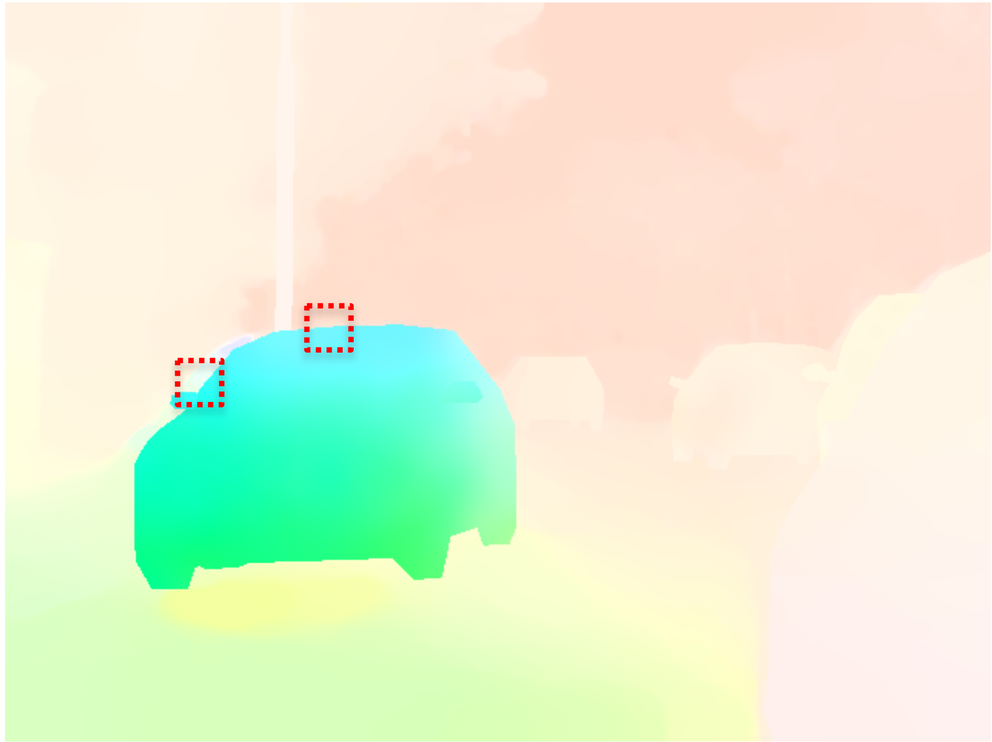


Slide credit: S. Lazebnik

Issue: Motion Boundaries

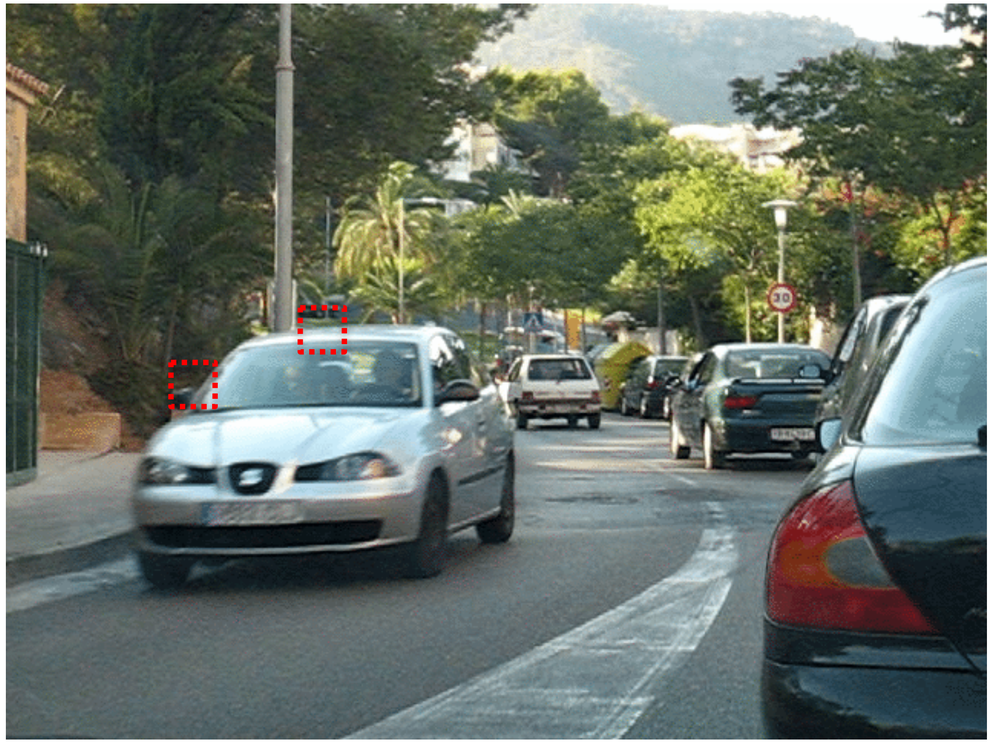
No matches can be found at motion boundaries…

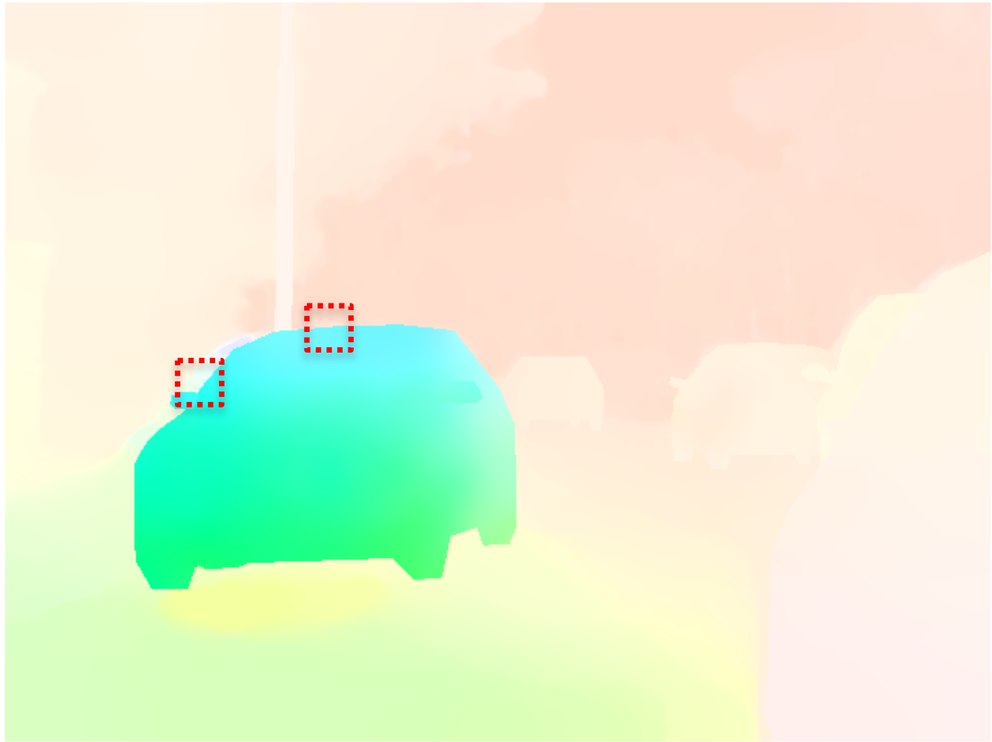




Issue: Motion Boundaries

No matches can be found at motion boundaries…





Issue: Ambiguous patch details

Flat regions of the image are underconstrained





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Flat regions of the image are underconstrained





Solving ambiguities: Horn & Schunck

Smoothness: neighboring pixels have similar motion



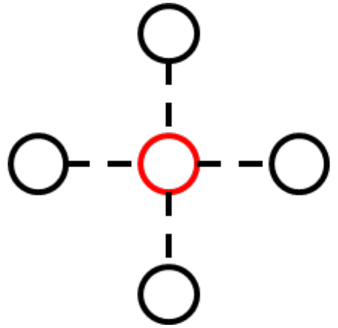


Solving ambiguities: Horn & Schunck

Smoothness: neighboring pixels have similar motion







Horn & Schunck



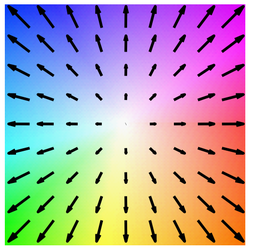
Input



Horn & Schunck



Ground truth



Color key
[Baker *et al.* IJCV'11]

Horn & Schunck



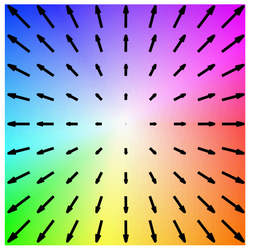
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Horn & Schunck



Ground truth



Color key
[Baker *et al.* IJCV'11]

Improving Horn & Schunck

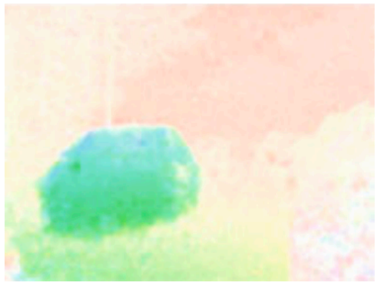
[Sun *et al.* CVPR'10, IJCV'14]

$$E(\mathbf{w}) = \sum_{\mathbf{p}} \left| I_t(\mathbf{p}) - I_{t+1}\left(\mathbf{p} + \mathbf{w}_\mathbf{p}\right) \right|^2 + \lambda \sum_{\mathbf{q} \in N_\mathbf{p}} \left| \mathbf{w}_\mathbf{p} - \mathbf{w}_\mathbf{q} \right|^2$$





"Old"



Multi-Scale Pyramid



Ground truth

Improving Horn & Schunck

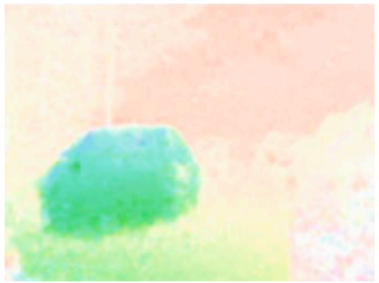
[Sun *et al.* CVPR'10, IJCV'14]

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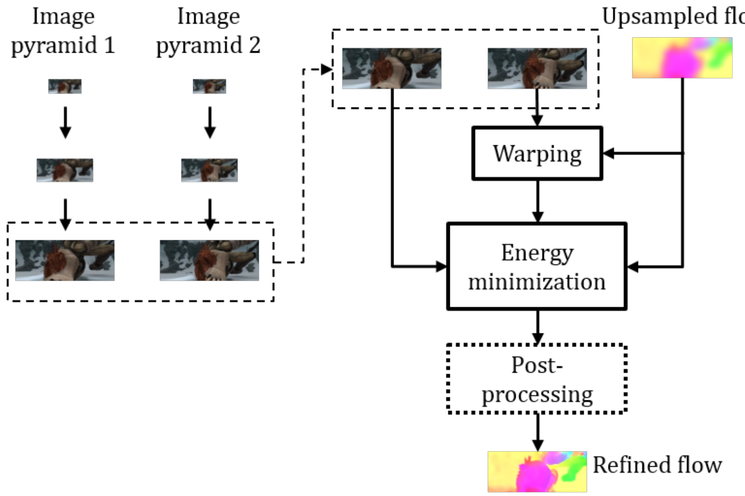




"Old"



Multi-Scale Pyramid





Ground truth

Improving Horn & Schunck

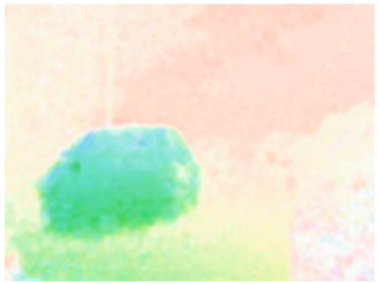
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"Old"



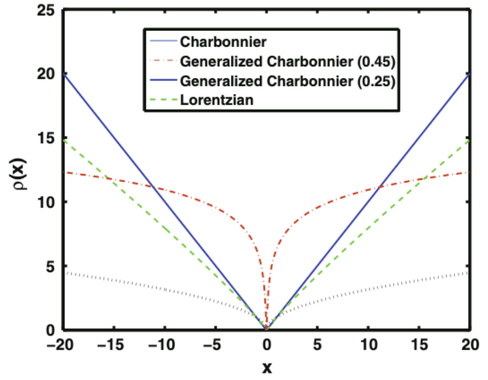
Multi-Scale Pyramid



Robust function



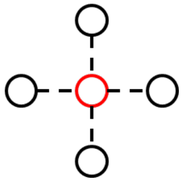
Ground truth



Improving Horn & Schunck

[Sun *et al.* CVPR'10, IJCV'14]

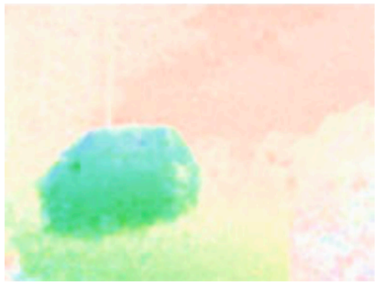
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"Old"



Multi-Scale Pyramid



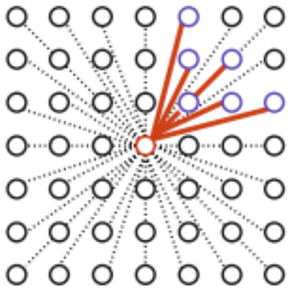
Robust function



Non-local term

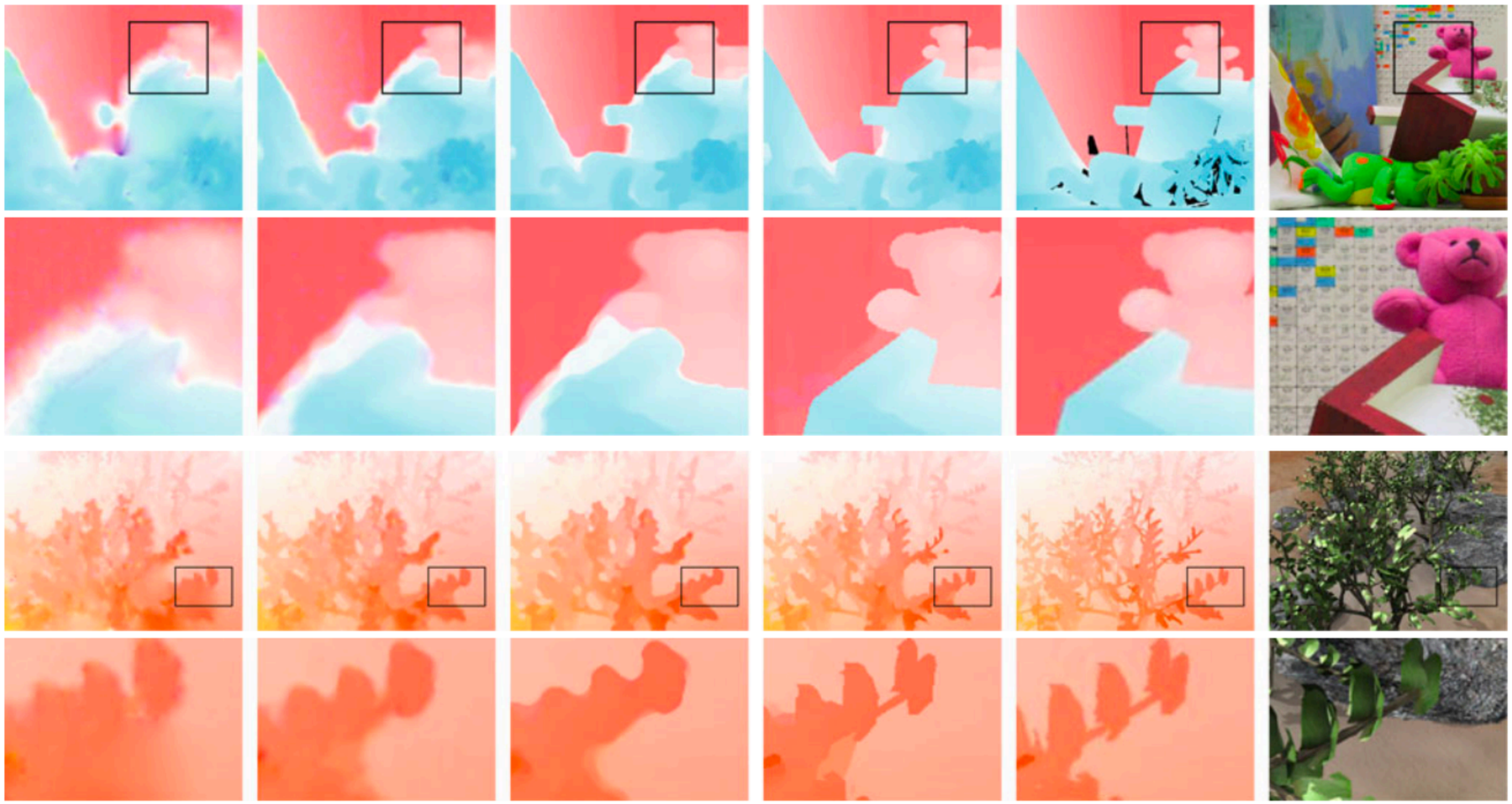


Ground truth



Improving Horn & Schunck

[Sun *et al.* CVPR'10, IJCV'14]



(a) "Old" **HS** [58] **(b)** "New" **HS** **(c)** **Classic++** **(d)** **Classic+NL** **(e)** Ground truth **(f)** First frame

Implementation Robust function Non-local smoothness term

Challenges for classical methods

Large motion
Motion blur
Occlusions
Lighting changes
Noise…

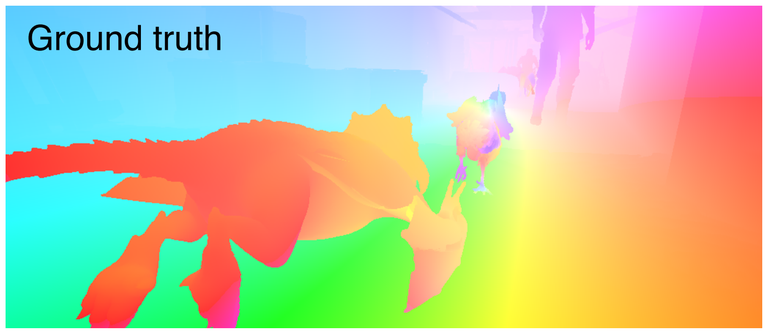
Hard to modify objective function and even harder to optimize it

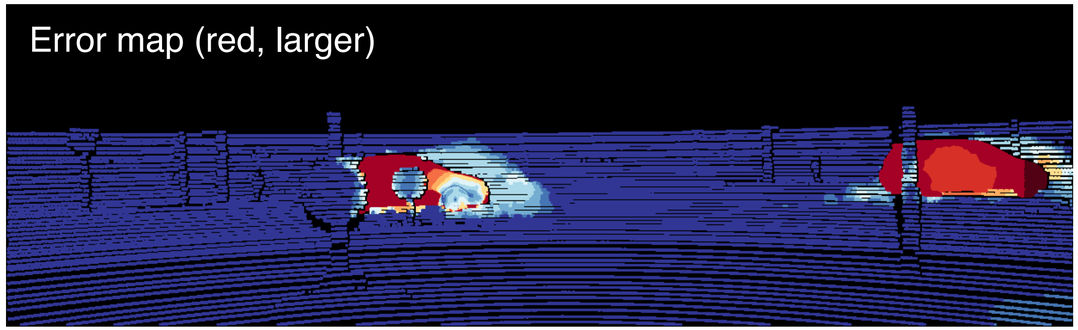












Challenges for classical methods

Large motion
Motion blur
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Lighting changes
Noise…

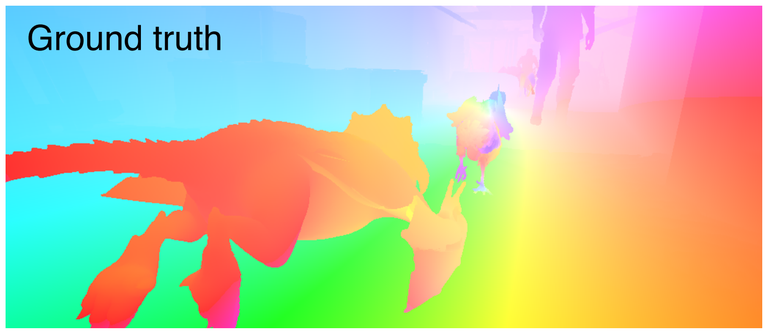
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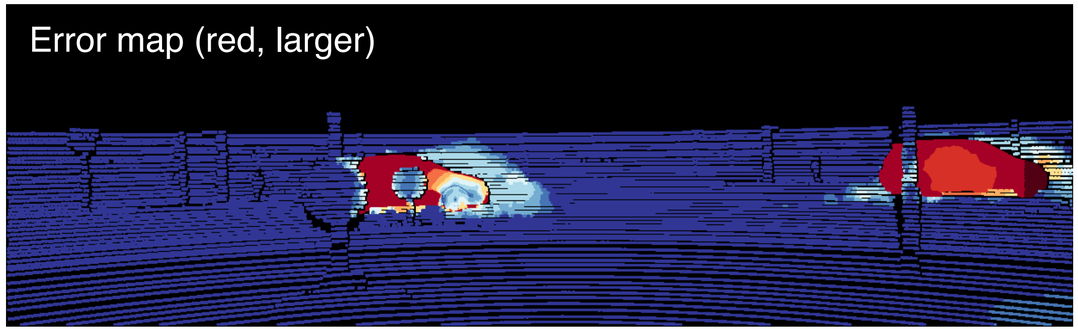












Summary

- Classical approach
  - Constancy assumption -> matching by comparison (cost volume)

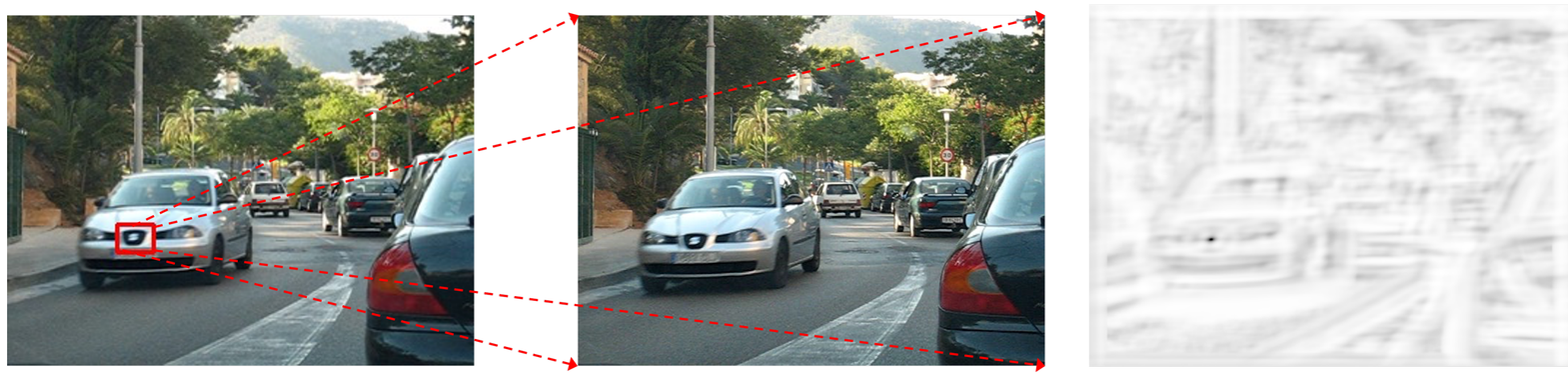
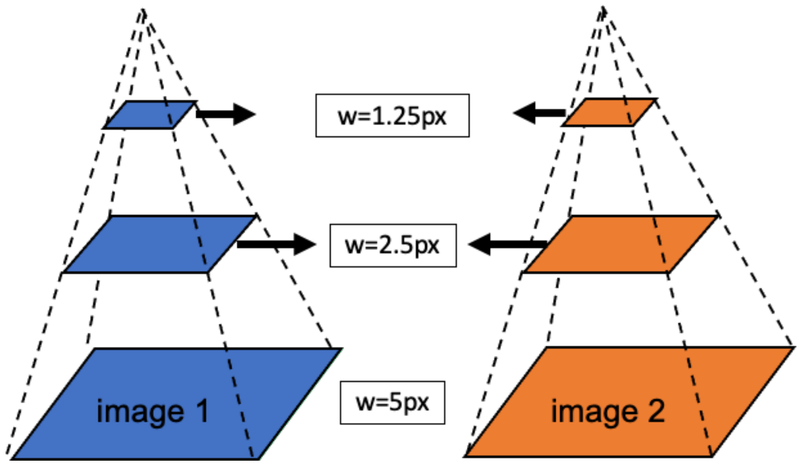


Image 1 Image 2 Cost volume

Summary

- Classical approach
  - Constancy assumption -> matching by comparison (cost volume)
  - Coarse-to-fine, warping-based iterative estimation





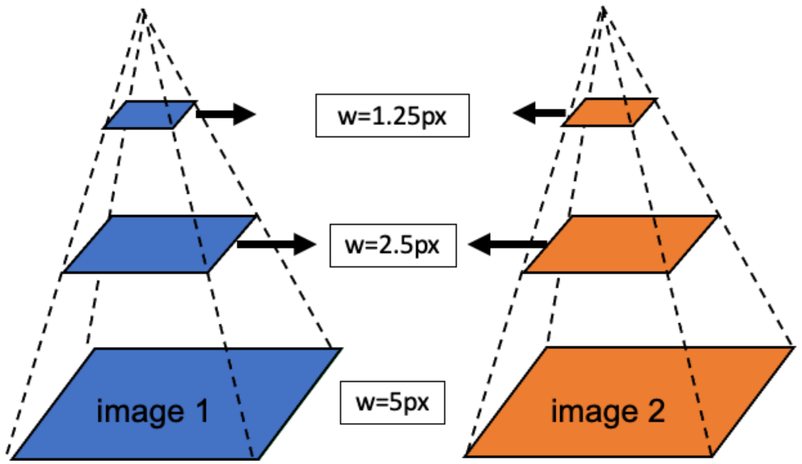
Input images *t* and *t*+1



Image *t* and warped image

Summary

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  - Constancy assumption -> matching by comparison (cost volume)
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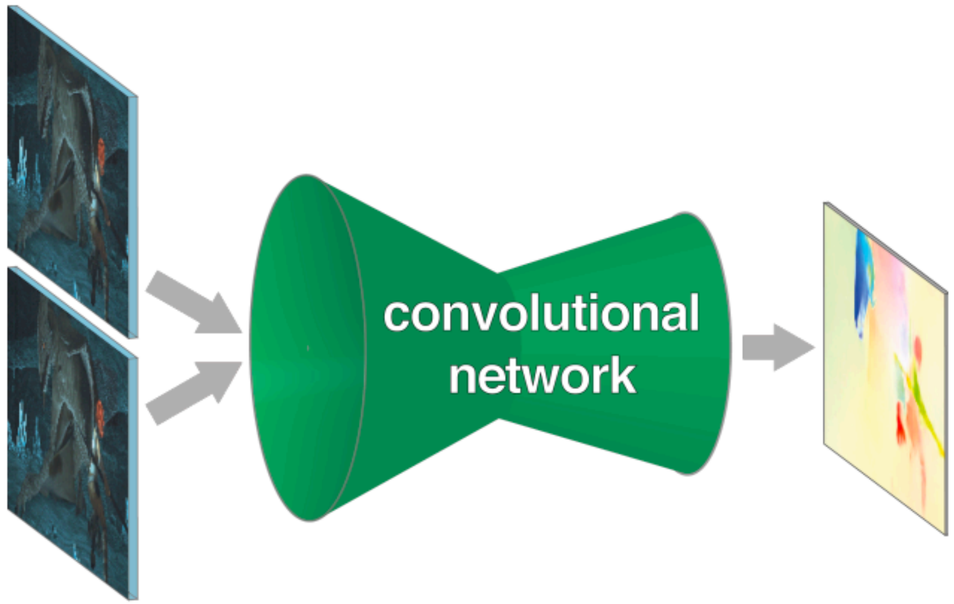
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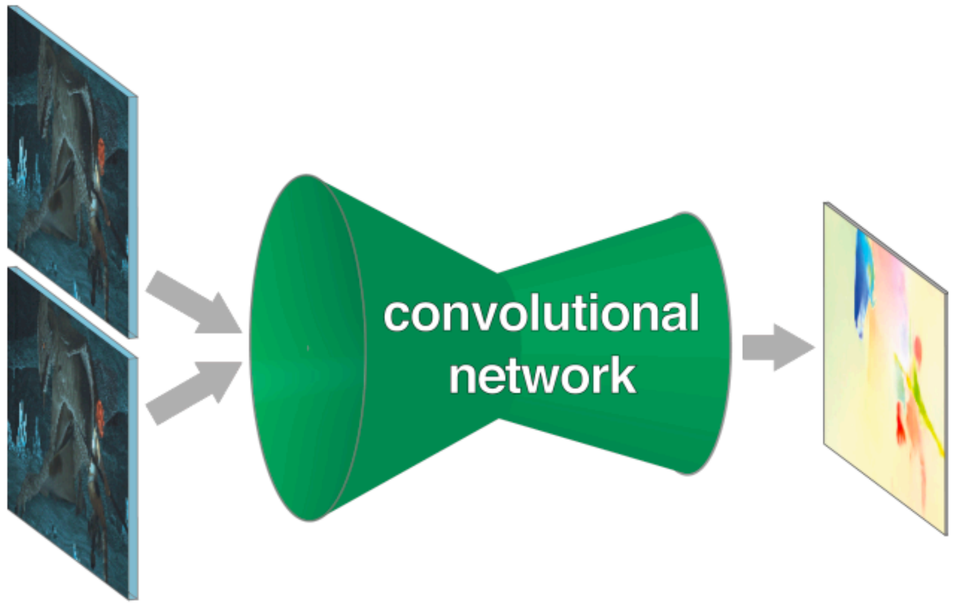
Supervised optical flow

[Dosovitskiy *et al.* ICCV'15]

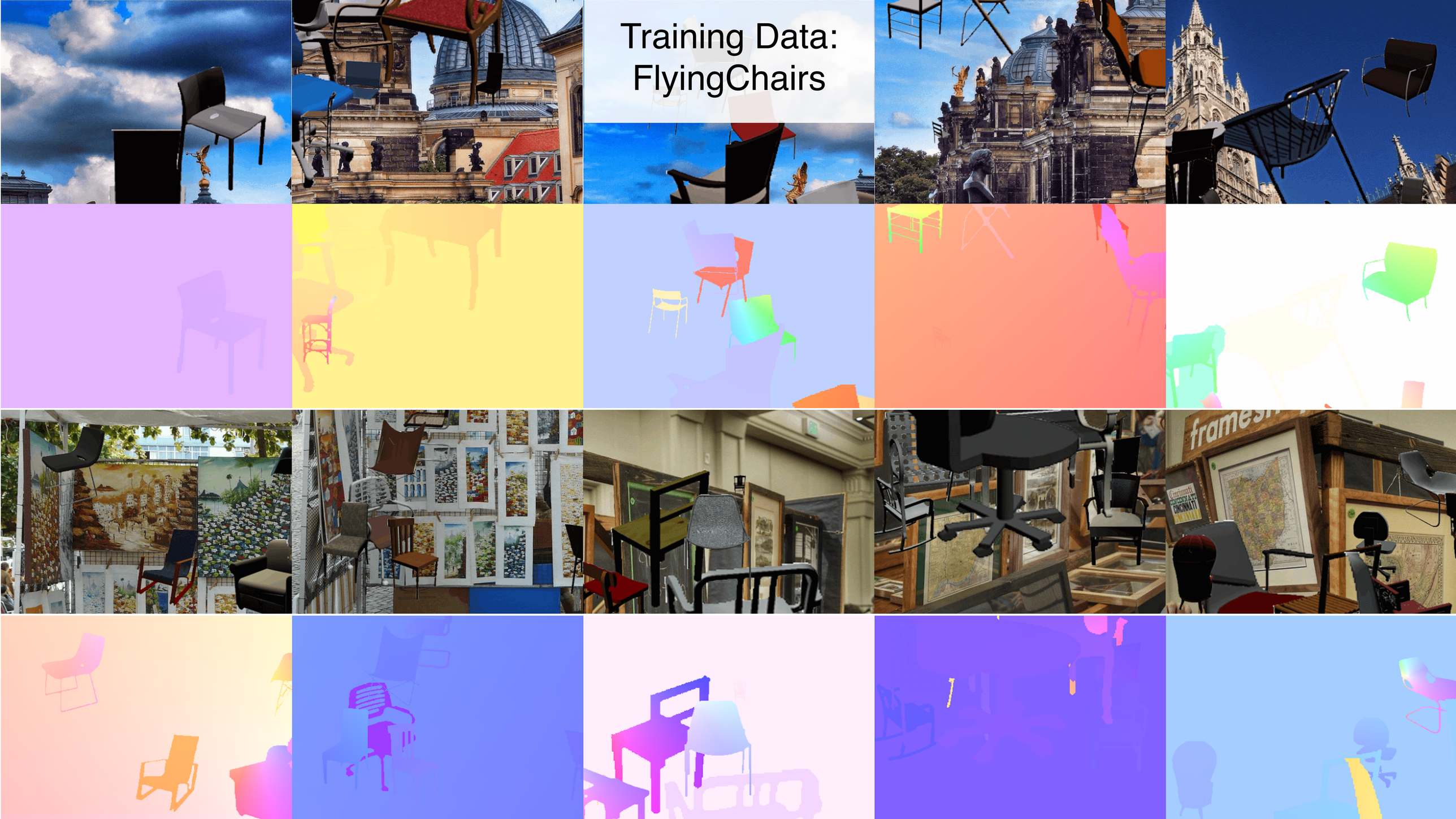


Supervised optical flow

[Dosovitskiy *et al.* ICCV'15]



What is the training/test data?


Training Data:
FlyingChairs

Two widely-used benchmarks for optical flow

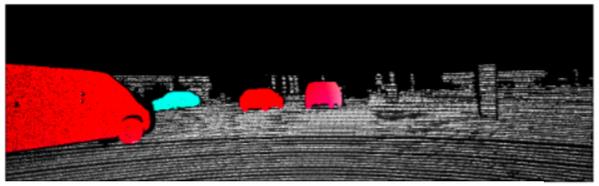
Sintel (Blender movie)



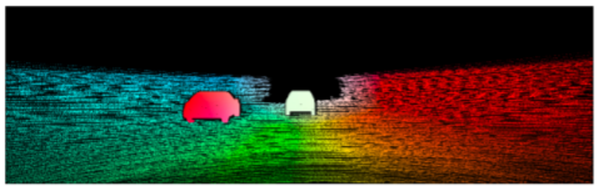


KITTI (driving)









Two widely-used benchmarks for optical flow

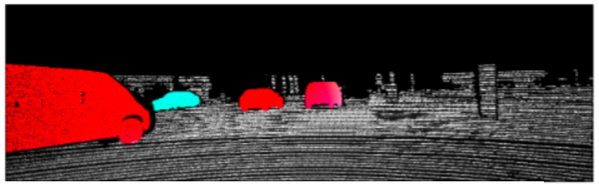
Sintel (Blender movie)



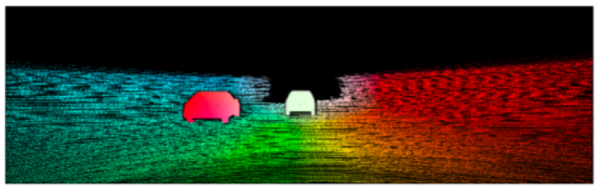


KITTI (driving)



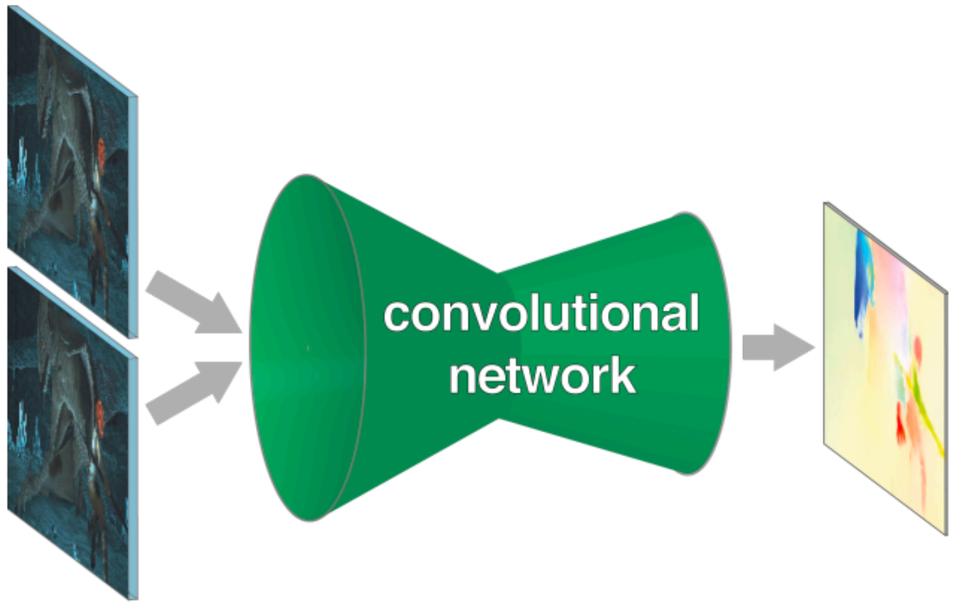






Supervised optical flow

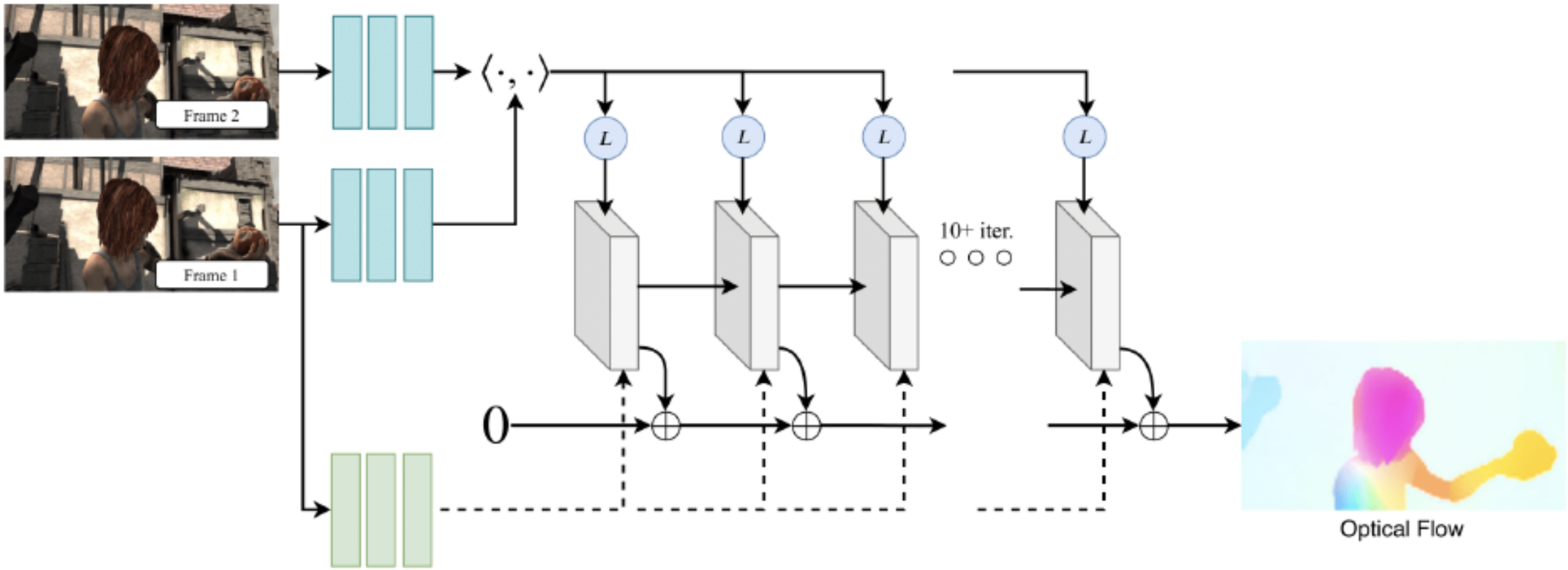
[Dosovitskiy *et al.* ICCV'15]



What is the network/architecture?

RAFT: Recurrent All-pairs Field Transforms

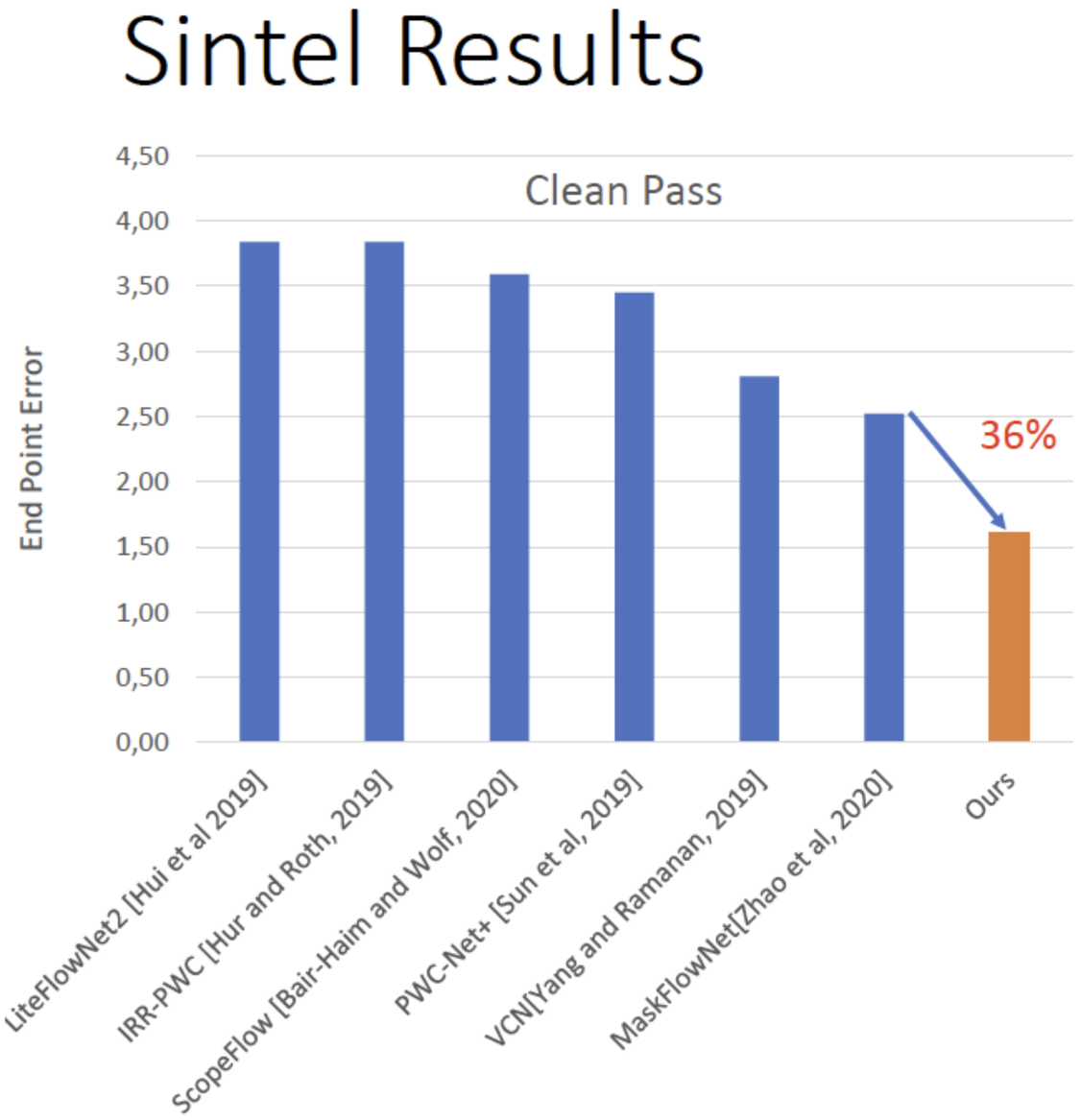
[Teed and Deng ECCV 2020 Best paper]



Slide credit: Teed and Deng

Significant improvement over prior art

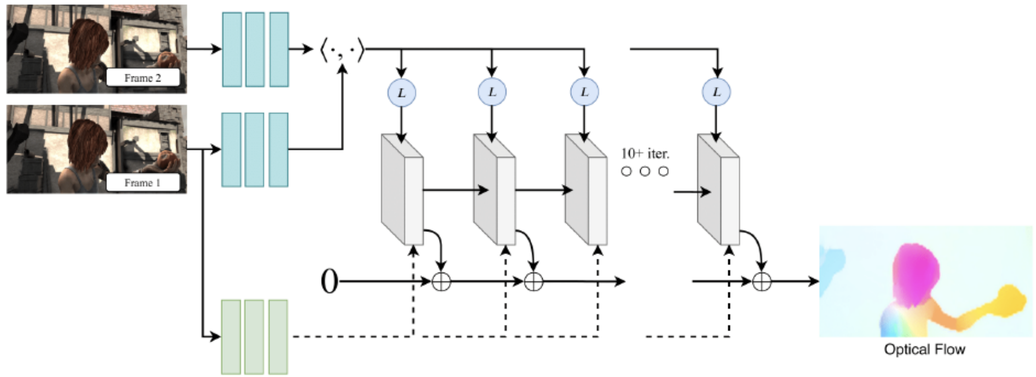
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Slide credit: Teed and Deng

RAFT: Recurrent All-pairs Field Transforms

[Teed and Deng ECCV 2020 Best paper]



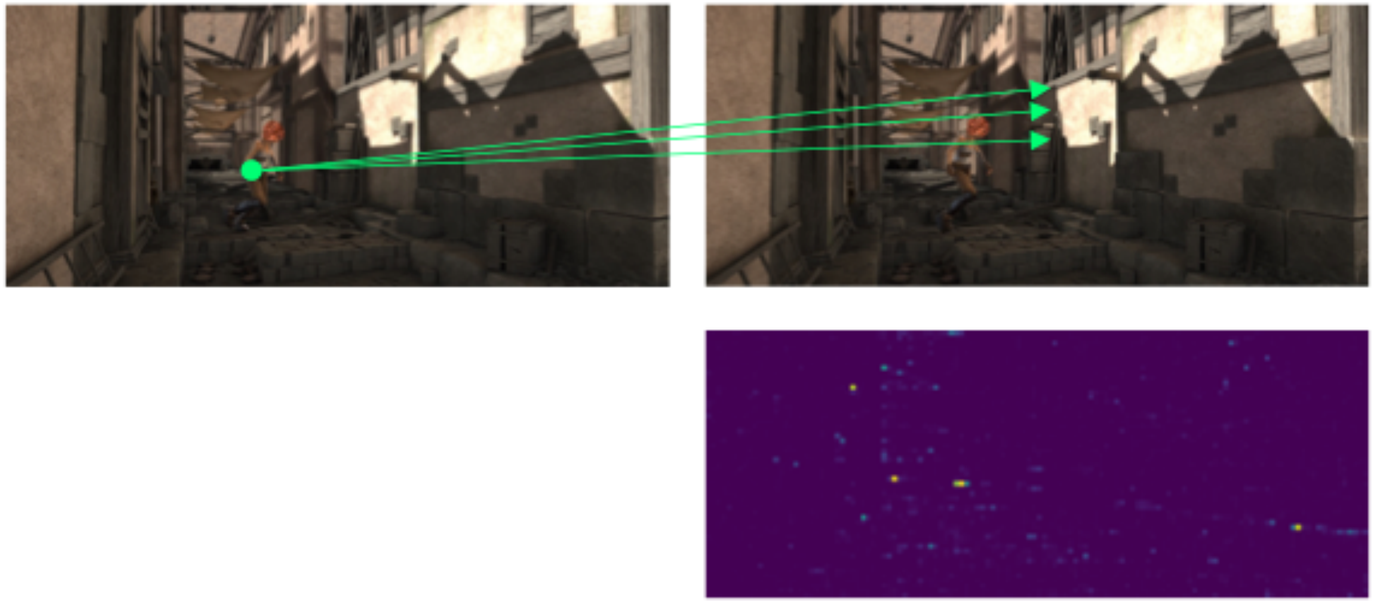
Key ideas

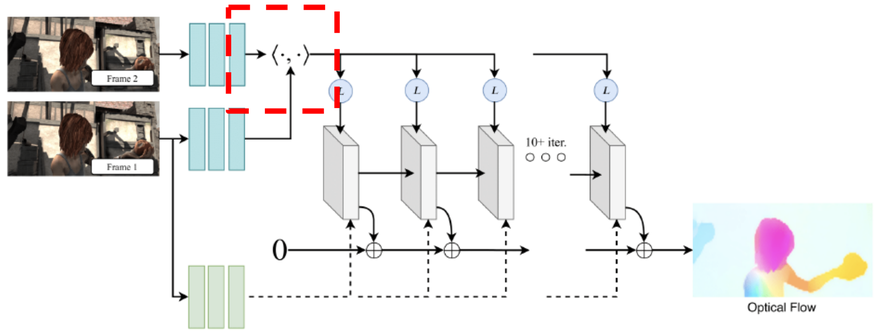
- All-pairs cost volume consistent across scales
- Recurrent module for iterative refinement of flow
- (Secret) Better training schemes

Slide credit: Teed and Deng

All-pairs visual similarity (cost volume)

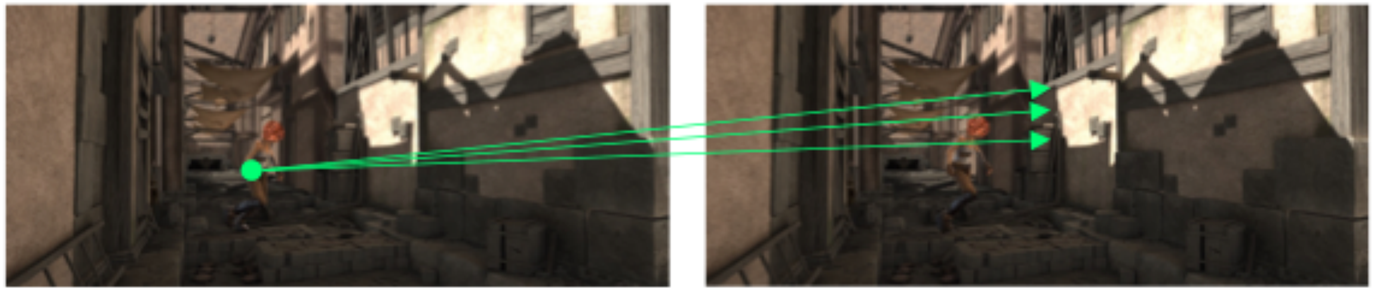
Inner product/correlation between features





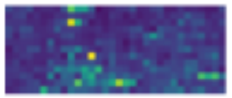
Cost volume pyramid

Spatial pooling

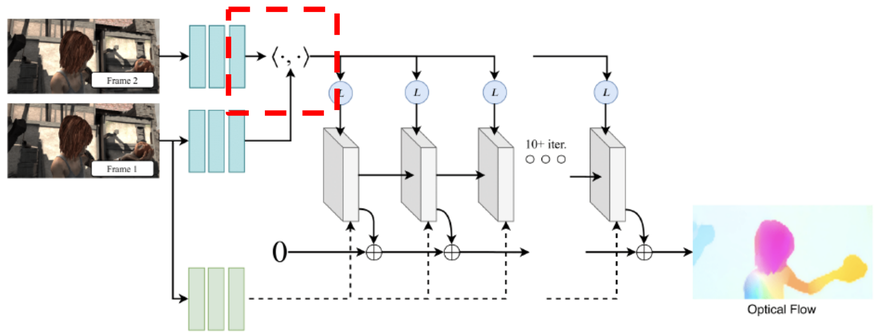








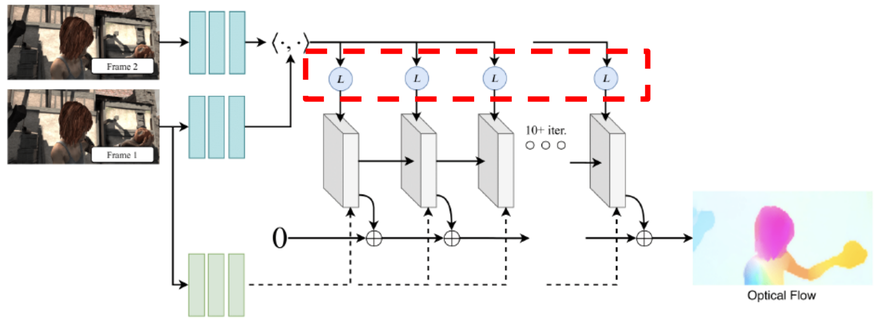


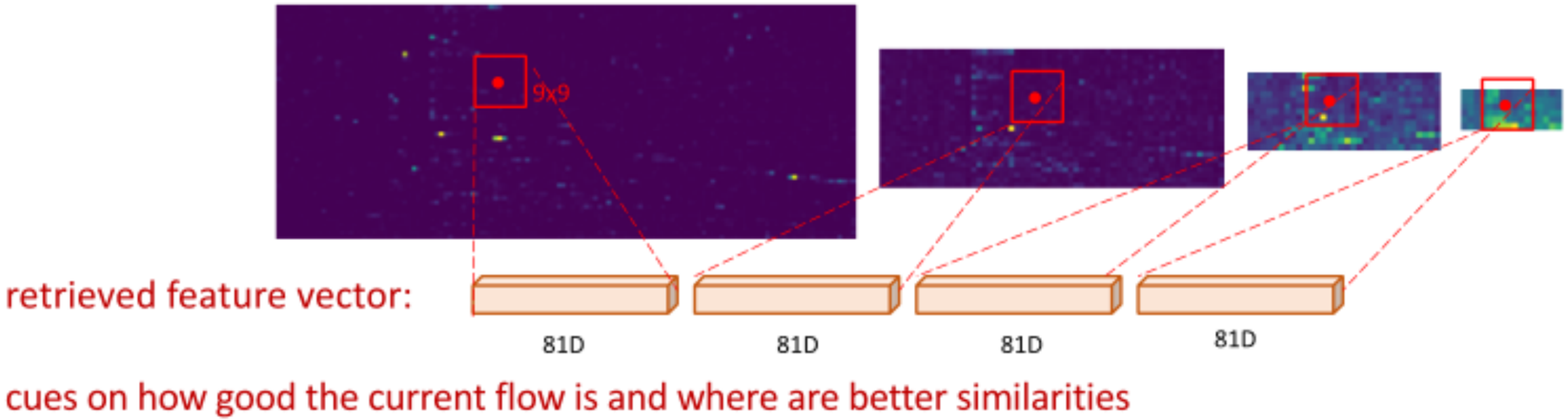


Look up cost volume

Retrieve using current motion estimates



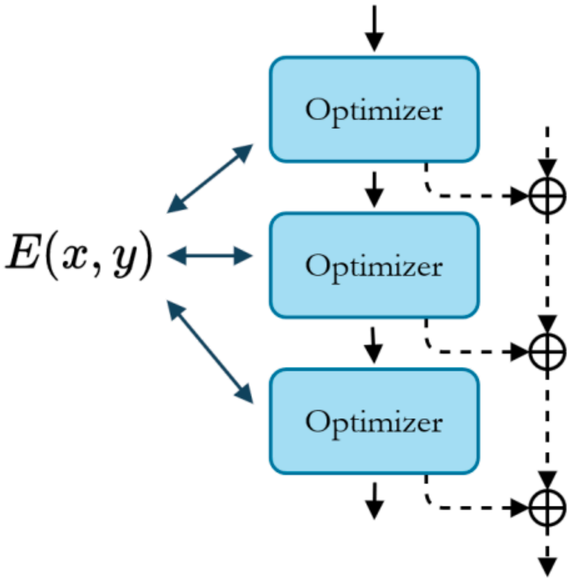


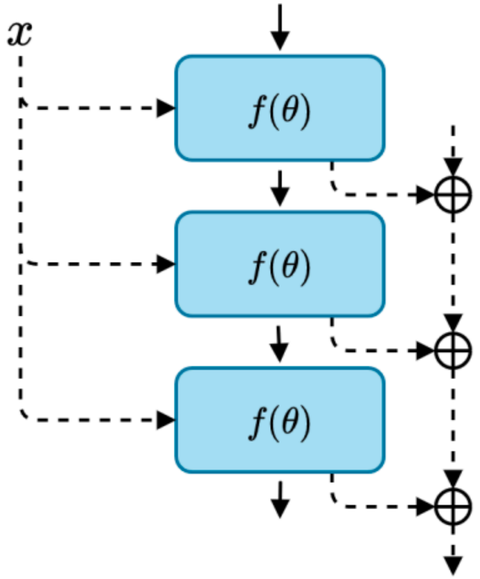


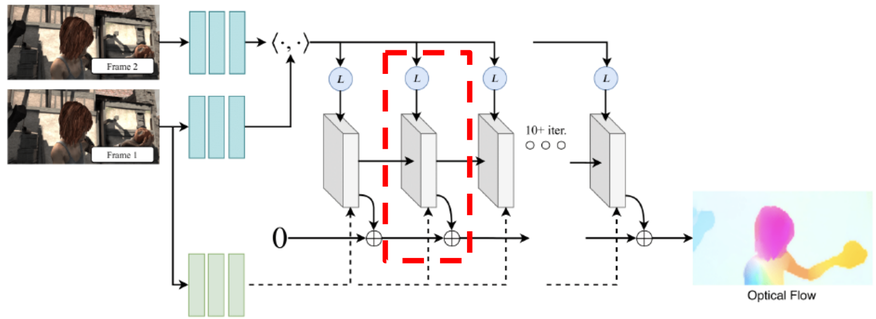
cues on how good the current flow is and where are better similarities

Recurrent update

Like classical optimization algorithms

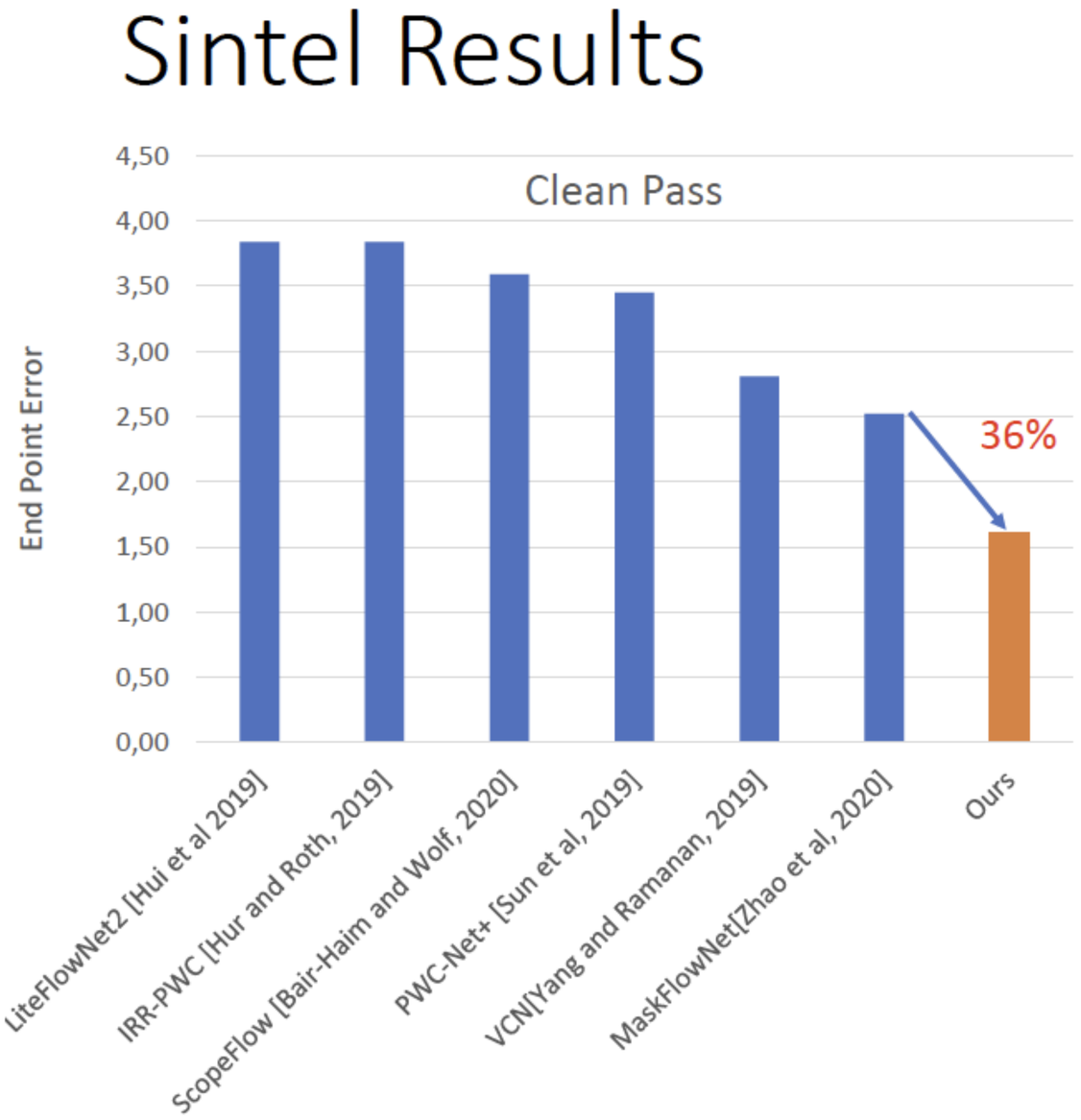






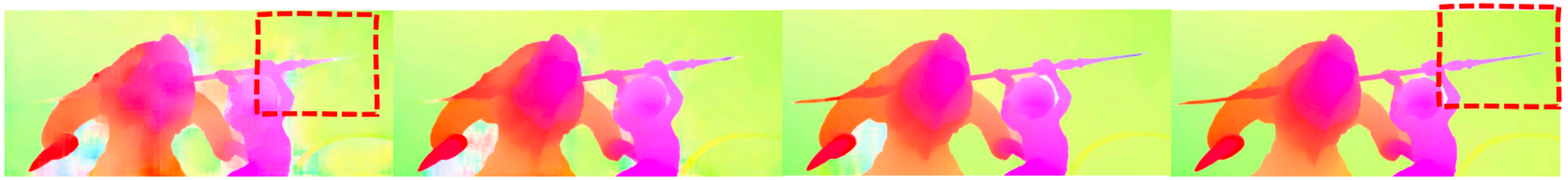
Significant improvement over prior art

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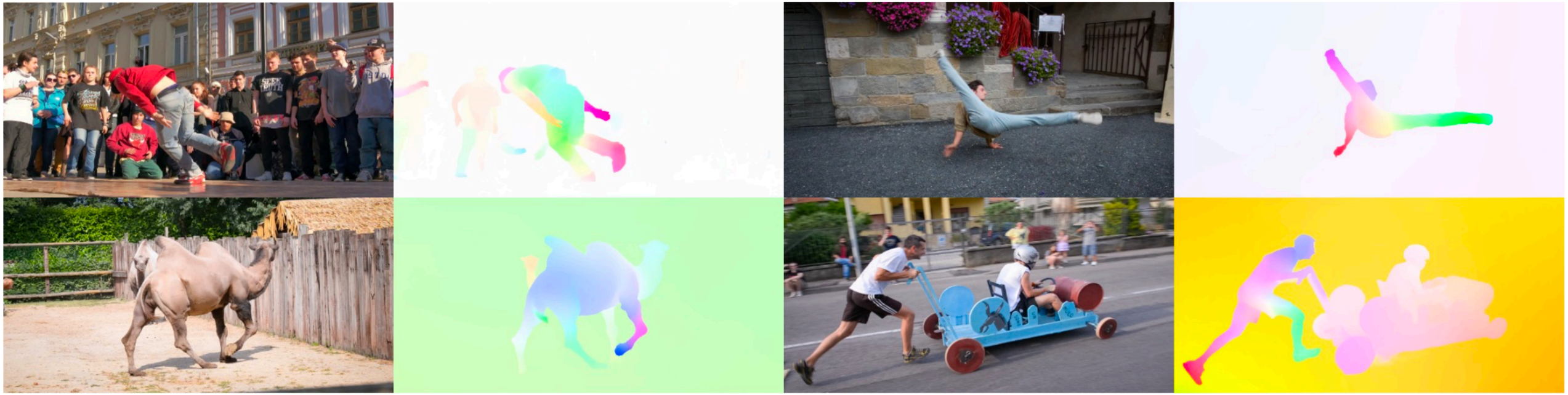
Slide credit: Teed and Deng

Recurrent update



1 Iteration | 2 Iterations | 5 Iterations | 32 Iterations

Visual results on Davis (real-world)



Is the hand-crafted structure (cost-volume, unrolled optimization on cost volume) really necessary?

The Surprising Effectiveness of Diffusion Models for Optical Flow and Monocular Depth Estimation

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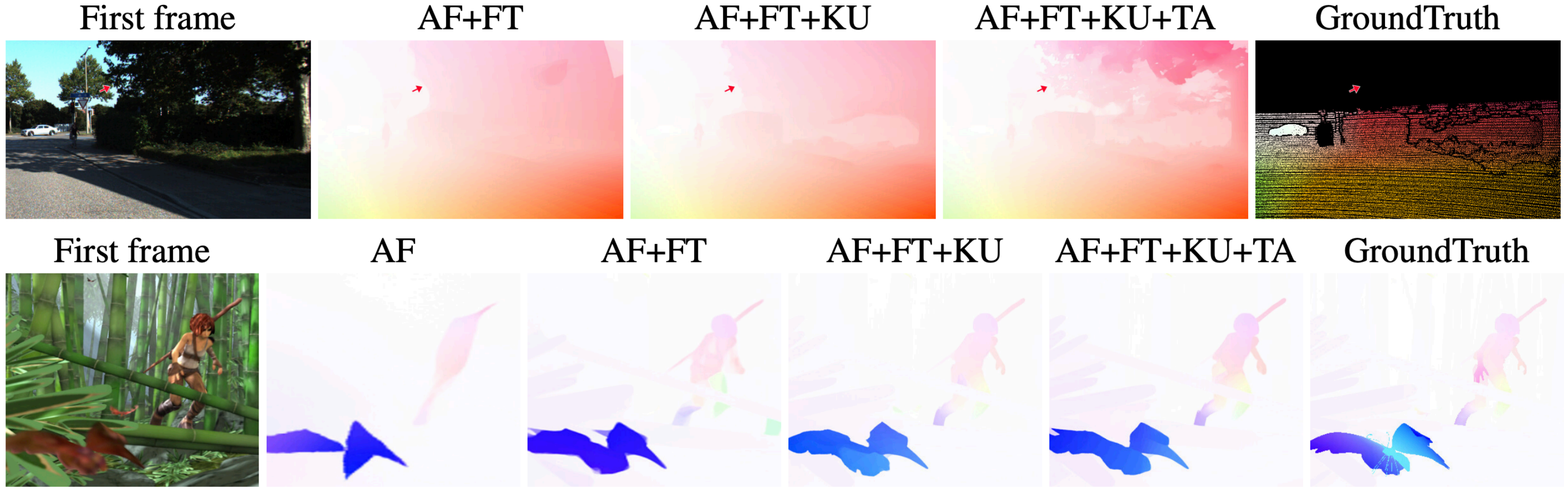
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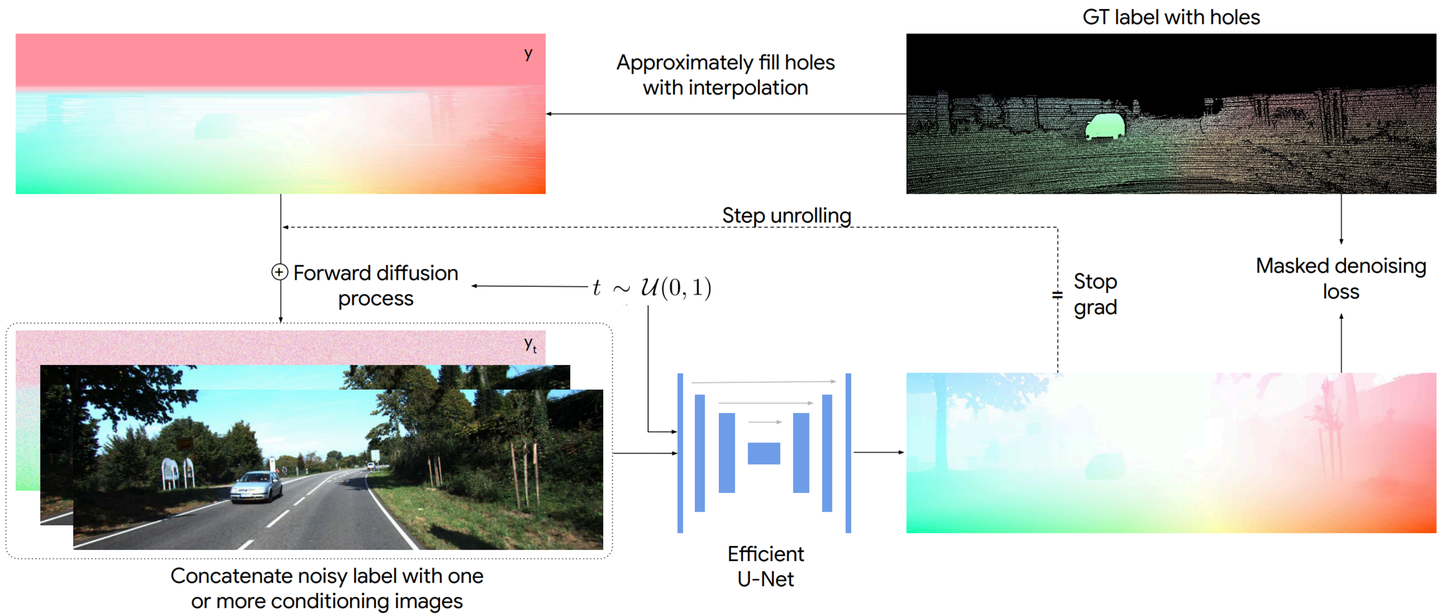
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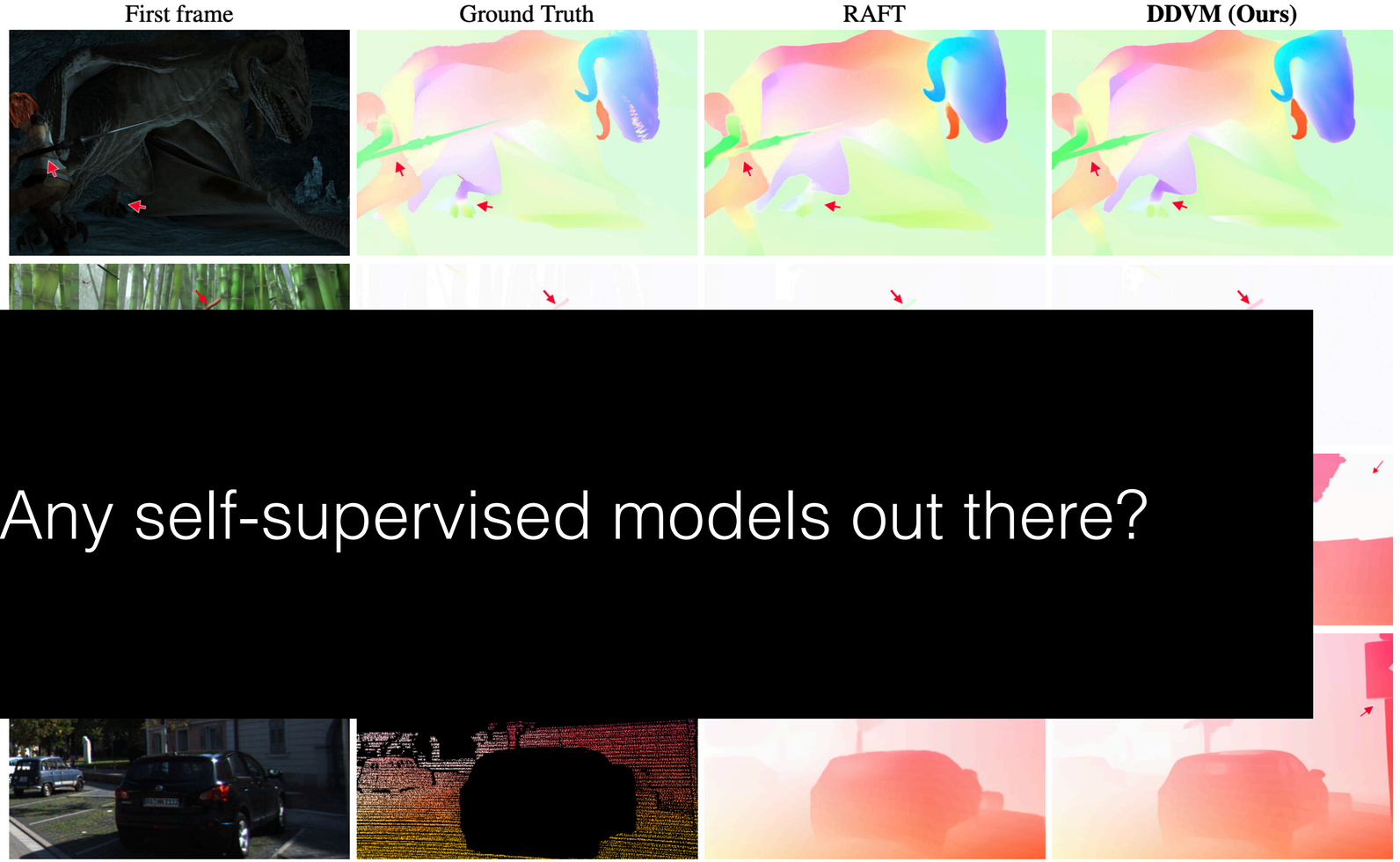
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Fully supervised… Any self-supervised models out there?

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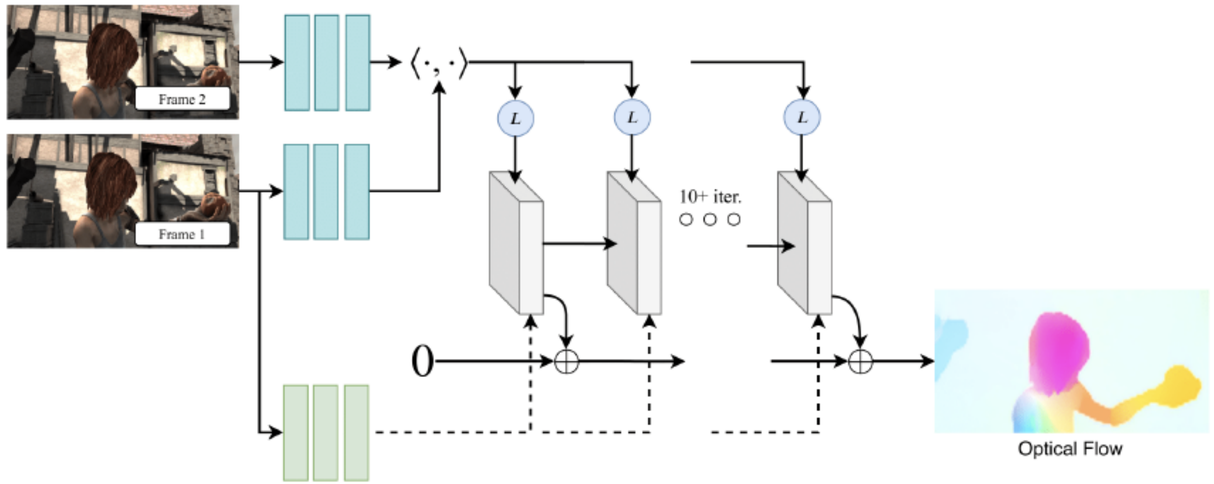
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Concepts of Self-Supervised Optical Flow

[Stone, Maurer et al. 2021, Jonschkowski et al. 2020, Meister et al. 2018, …]
(see SMURF for good discussion!)

Concepts of Self-Supervised Optical Flow

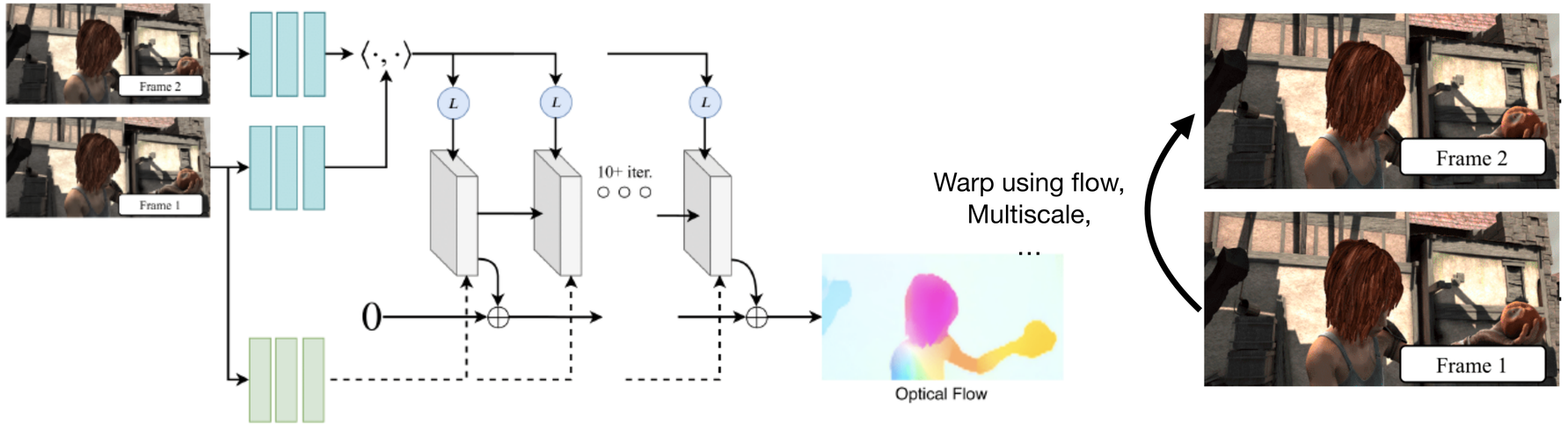
[Stone, Maurer et al. 2021, Jonschkowski et al. 2020, Meister et al. 2018, …]
(see SMURF for good discussion!)



Estimate flow with Neural Network…

Concepts of Self-Supervised Optical Flow

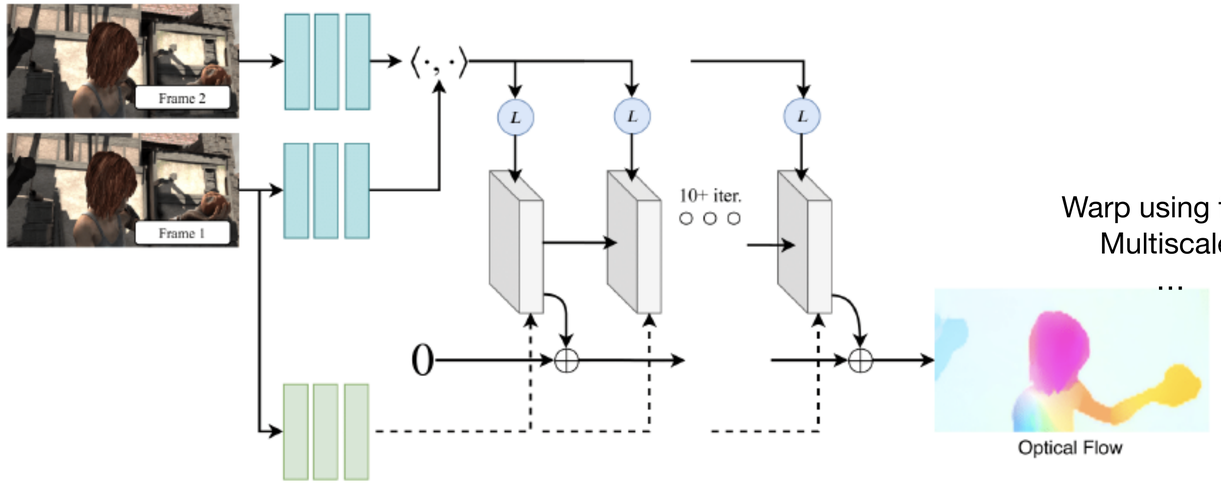
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(see SMURF for good discussion!)



Estimate flow with Neural Network…

Concepts of Self-Supervised Optical Flow

[Stone, Maurer et al. 2021, Jonschkowski et al. 2020, Meister et al. 2018, …]
(see SMURF for good discussion!)



Warp using flow,
Multiscale,
…



$$\sum_{\mathbf{p}} \left| I_t(\mathbf{p}) - I_{t+1}\left(\mathbf{p} + \mathbf{w}_\mathbf{p}\right) \right|^2$$
$$+\lambda \sum_{\mathbf{q} \in N_p} \left| \mathbf{w}_\mathbf{p} - \mathbf{w}_\mathbf{q} \right|^2$$
$$+ \ldots$$

Estimate flow with Neural Network…

…but *supervise* flow with warping-based losses & regularizers!

Teacher-Student for Optical Flow

This CVPR 2021 paper is the Open Access version, provided by the Computer Vision Foundation.
Except for this watermark, it is identical to the accepted version;
the final published version of the proceedings is available on IEEE Xplore.

SMURF: Self-Teaching Multi-Frame Unsupervised RAFT with Full-Image Warping

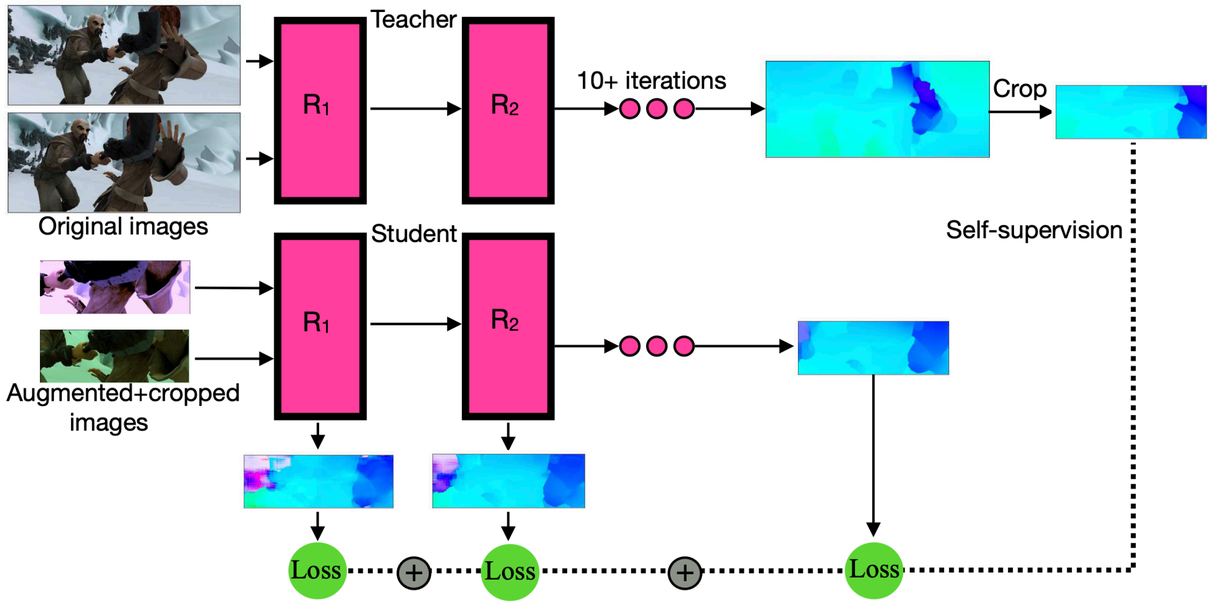
Austin Stone*[1] Daniel Maurer*[2] Alper Ayvaci[2] Anelia Angelova[1] Rico Jonschkowski[1]
[1]Robotics at Google [2]Waymo
{austinstone, anelia, rjon}@google.com {maurerd, ayvaci}@waymo.com
https://github.com/google-research/google-research/tree/master/smurf

Abstract

We present SMURF, a method for unsupervised learning of optical flow that improves state of the art on all benchmarks by 36% to 40% (over the prior best method UFlow) and even outperforms several supervised approaches such as PWC-Net and FlowNet2. Our method integrates architecture improvements from supervised optical flow, i.e. the RAFT model, with new ideas for unsupervised learning that include a sequence-aware self-supervision loss, a technique for handling out-of-frame motion, and an approach for learning effectively from multi-frame video data while still only requiring two frames for inference.

Unsupervised learning is a promising direction to address this issue as it allows training optical flow models from unlabeled videos of any domain. The unsupervised approach works by combining ideas from classical methods and supervised-learning – training the same neural networks as in supervised approaches but optimizing them with objectives such as smoothness and photometric similarity from classical methods. Unlike those classical methods, unsupervised approaches perform optimization not per image pair but jointly for the entire training set.

Since unsupervised optical flow takes inspiration from classical and supervised learning methods, we can make substantial progress by properly combining novel ideas with insights from these two directions. In this paper, we do exactly that and make the following three contributions:



Motivation:

1. The model learns to ignore photometric augmentations
2. The model learns to make better predictions at the borders and in occluded areas of the image (with other tricks, see paper)
3. Early iterations of the recurrent model learn from the output at the final iteration

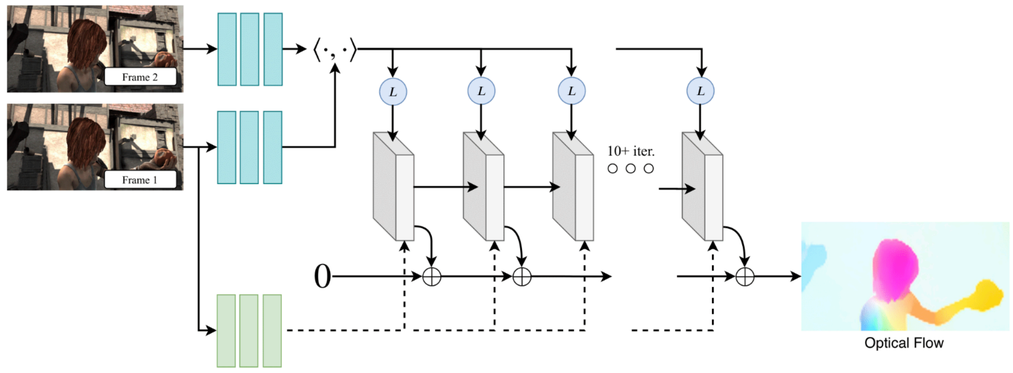
Two principles of Motion Estimation

Two principles of Motion Estimation

Optical Flow

Dense correspondences between a pair of frames

RAFT



Particle Video Revisited: Tracking Through Occlusions Using Point Trajectories. Harley et. al. ECCV 2022
TAP-Vid: A Benchmark for Tracking Any Point in a Video. Doersch et al., NeurIPS D&B 2022
RAFT: Recurrent All-Pairs Field Transforms for Optical Flow. Teed et al. , ECCV 2020

Two principles of Motion Estimation

Two principles of Motion Estimation

Point Tracking

Long-term tracking of individual points

Two principles of Motion Estimation

Optical Flow

Dense correspondences between a pair of frames

Point Tracking

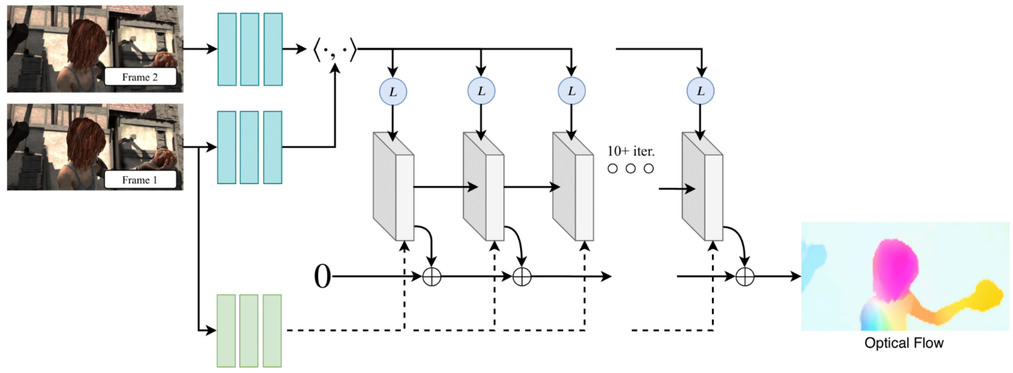
Long-term tracking of individual points

Two principles of Motion Estimation

Optical Flow

Dense correspondences between a pair of frames

RAFT



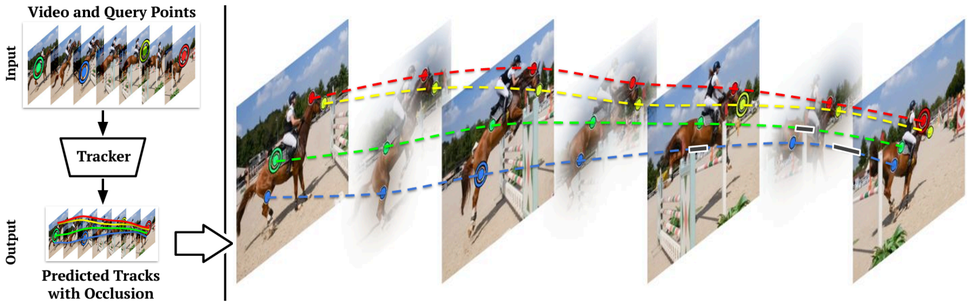
Point Tracking

Long-term tracking of individual points

PIPs



TAP-Net



Particle Video Revisited: Tracking Through Occlusions Using Point Trajectories. Harley et. al. ECCV 2022
TAP-Vid: A Benchmark for Tracking Any Point in a Video. Doersch et al., NeurIPS D&B 2022
RAFT: Recurrent All-Pairs Field Transforms for Optical Flow. Teed et al. , ECCV 2020

2207.12153v2 [cs.CV] 25 Jul 2022

Particle Video Revisited: Tracking Through Occlusions Using Point Trajectories

Adam W. Harley, Zhaoyuan Fang, and Katerina Fragkiadaki

Carnegie Mellon University
{aharley, zhaoyuaf, katef}@cs.cmu.edu
Project page: https://particle-video-revisited.github.io

Abstract. Tracking pixels in videos is typically studied as an optical flow estimation problem, where every pixel is described with a displacement vector that locates it in the next frame. Even though wider temporal context is freely available, prior efforts to take this into account have yielded only small gains over 2-frame methods. In this paper, we revisit Sand and Teller's "particle video" approach, and study pixel tracking as a long-range motion estimation problem, where every pixel is described with a trajectory that locates it in multiple future frames. We re-build this classic approach using components that drive the current state-of-the-art in flow and object tracking, such as dense cost maps, iterative optimization, and learned appearance updates. We train our models using long-range amodal point trajectories mined from existing optical flow data that we synthetically augment with multi-frame occlusions. We test our approach in trajectory estimation benchmarks and in keypoint label propagation tasks, and compare favorably against state-of-the-art optical flow and feature tracking methods.

Particle Video Revisited

Initialize positions and features

(x_1, y_1)



(1,2)

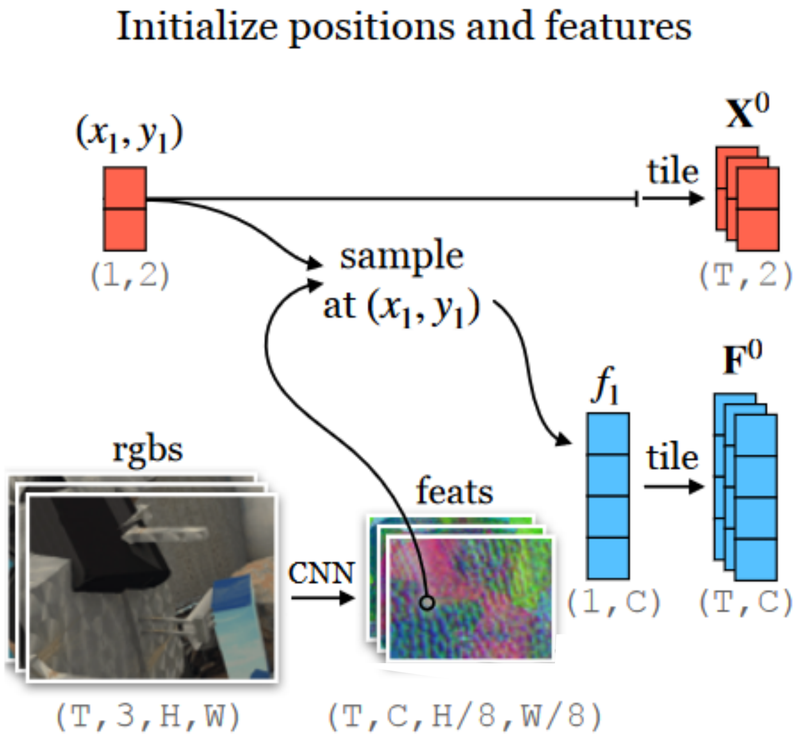
rgbs



(T,3,H,W)

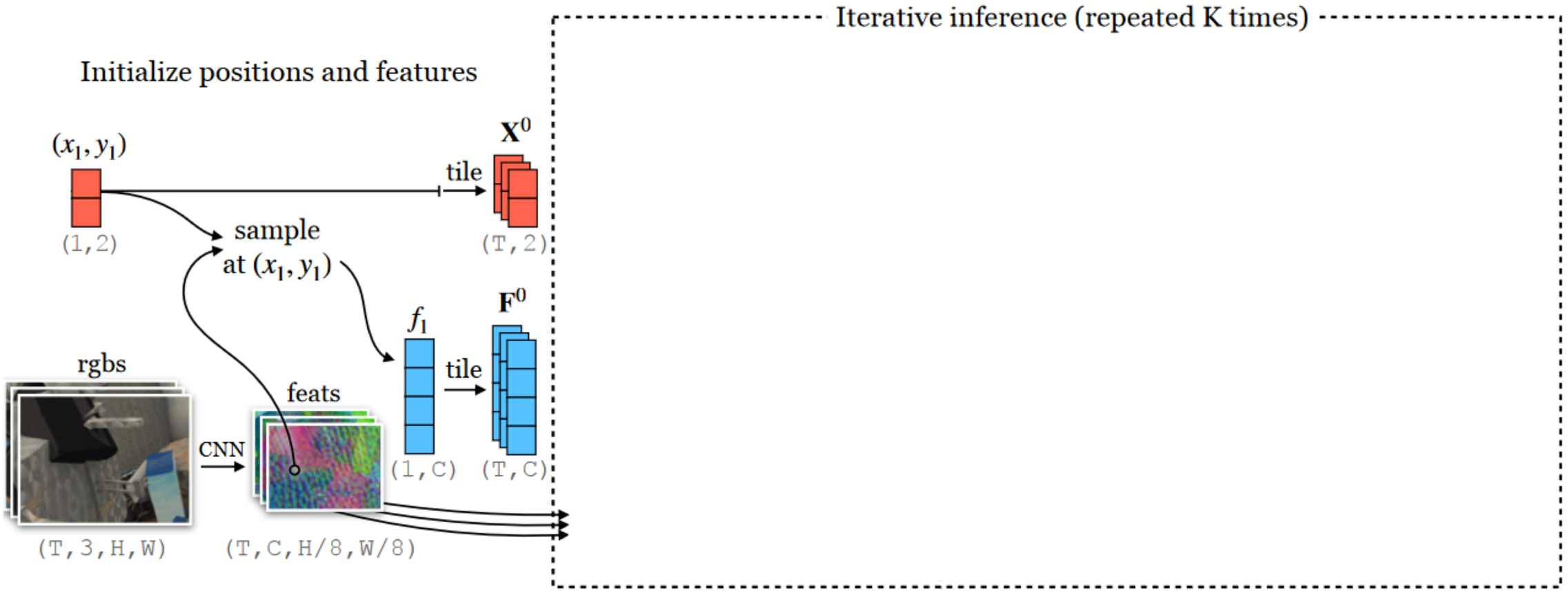
Particle Video Revisited: Tracking Through Occlusions Using Point Trajectories. Harley et. al. ECCV 2022

Particle Video Revisited



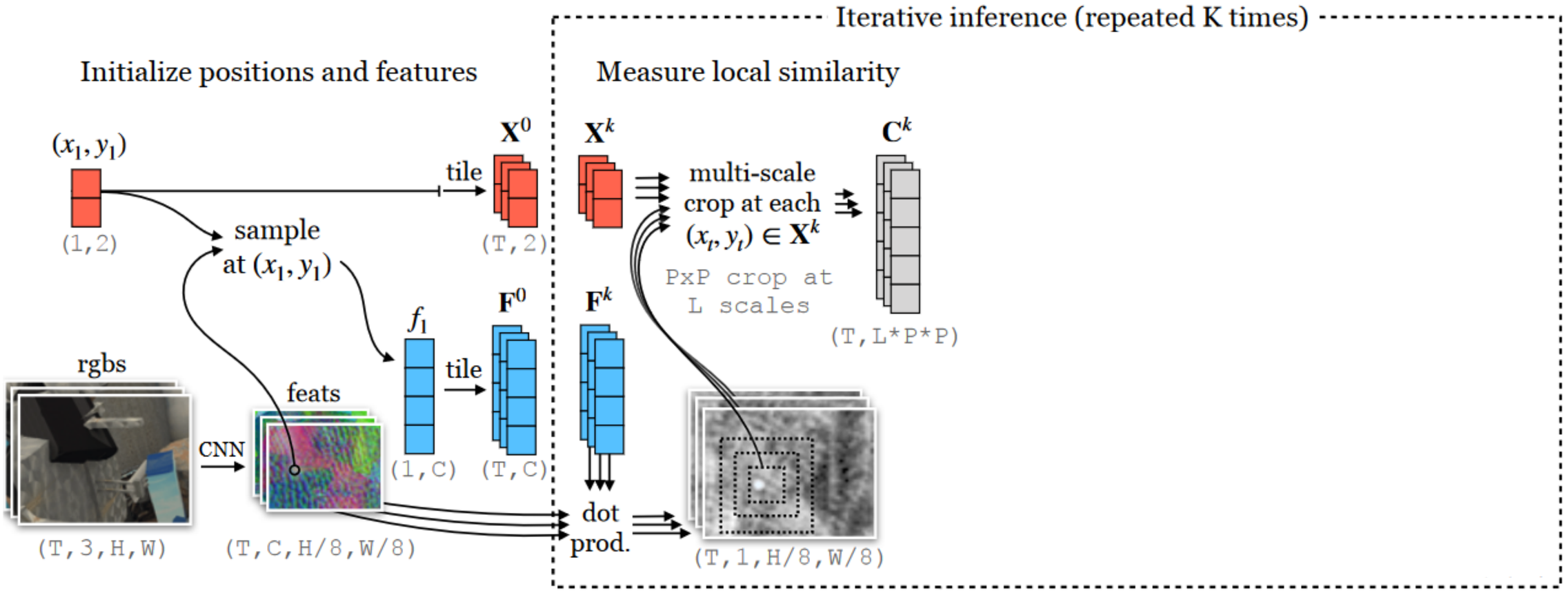
Particle Video Revisited: Tracking Through Occlusions Using Point Trajectories. Harley et. al. ECCV 2022

Particle Video Revisited



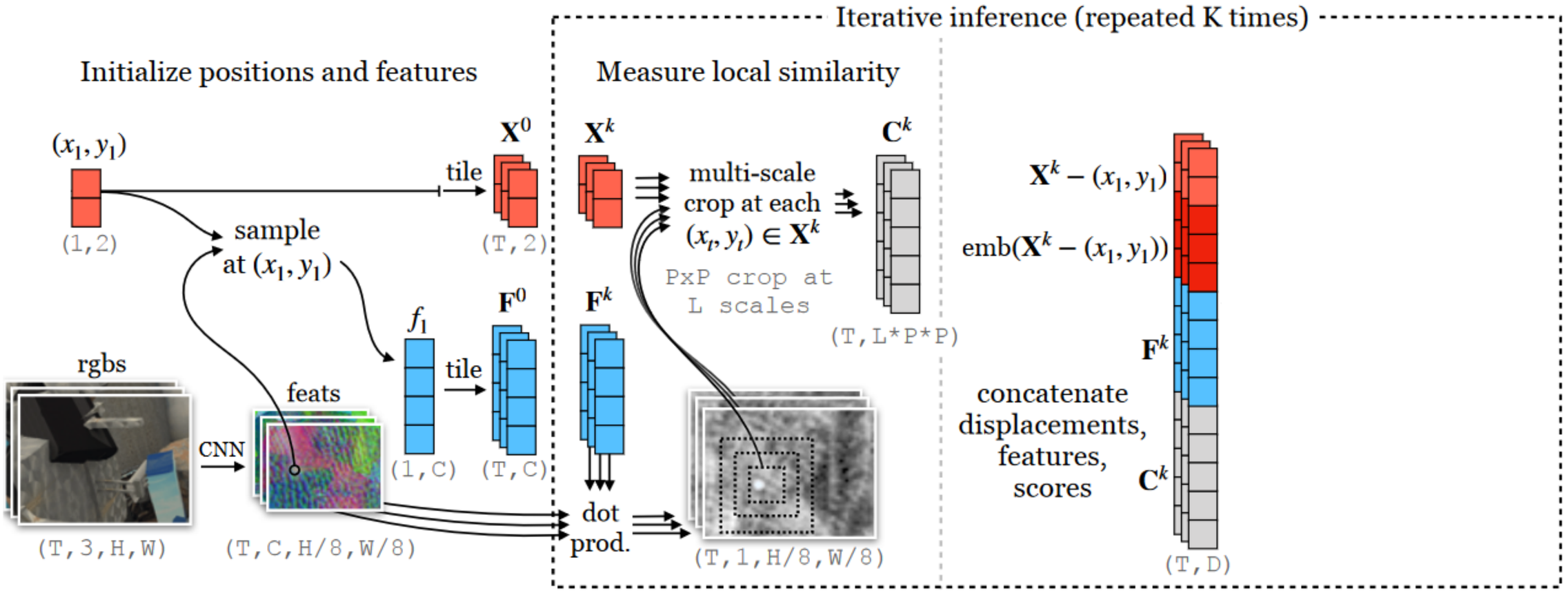
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Particle Video Revisited



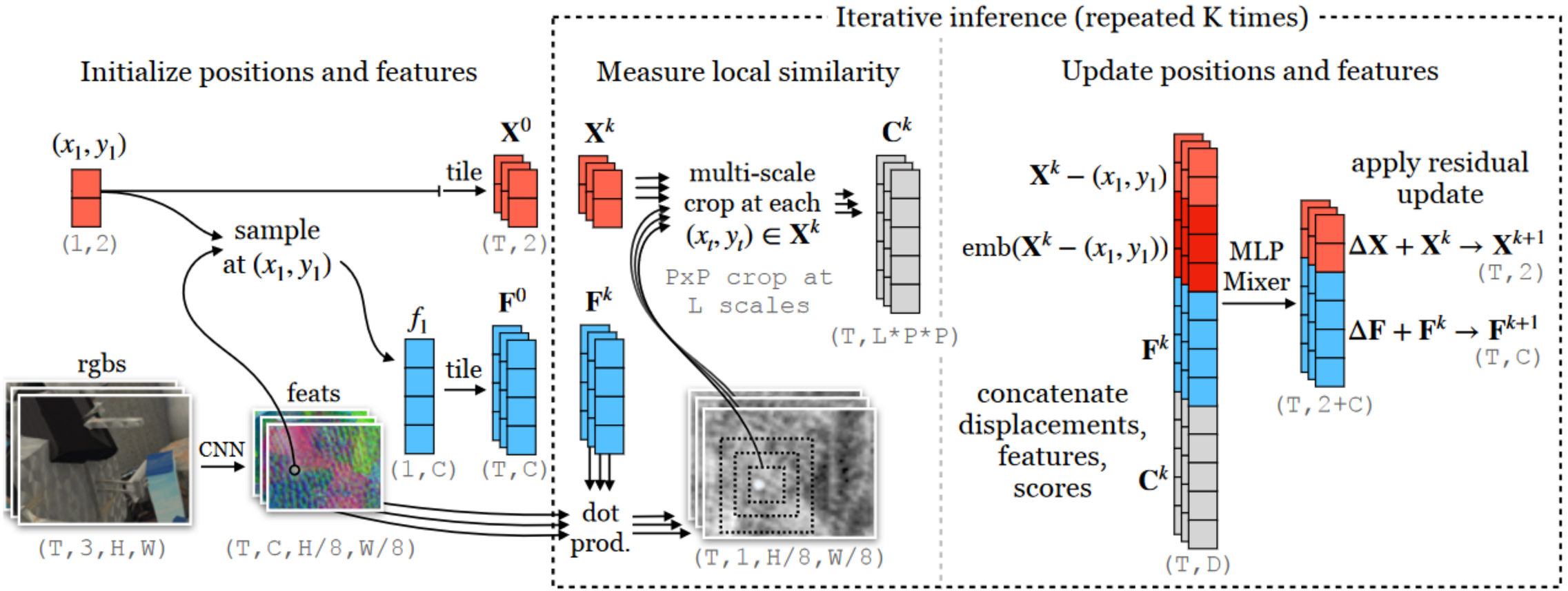
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Particle Video Revisited



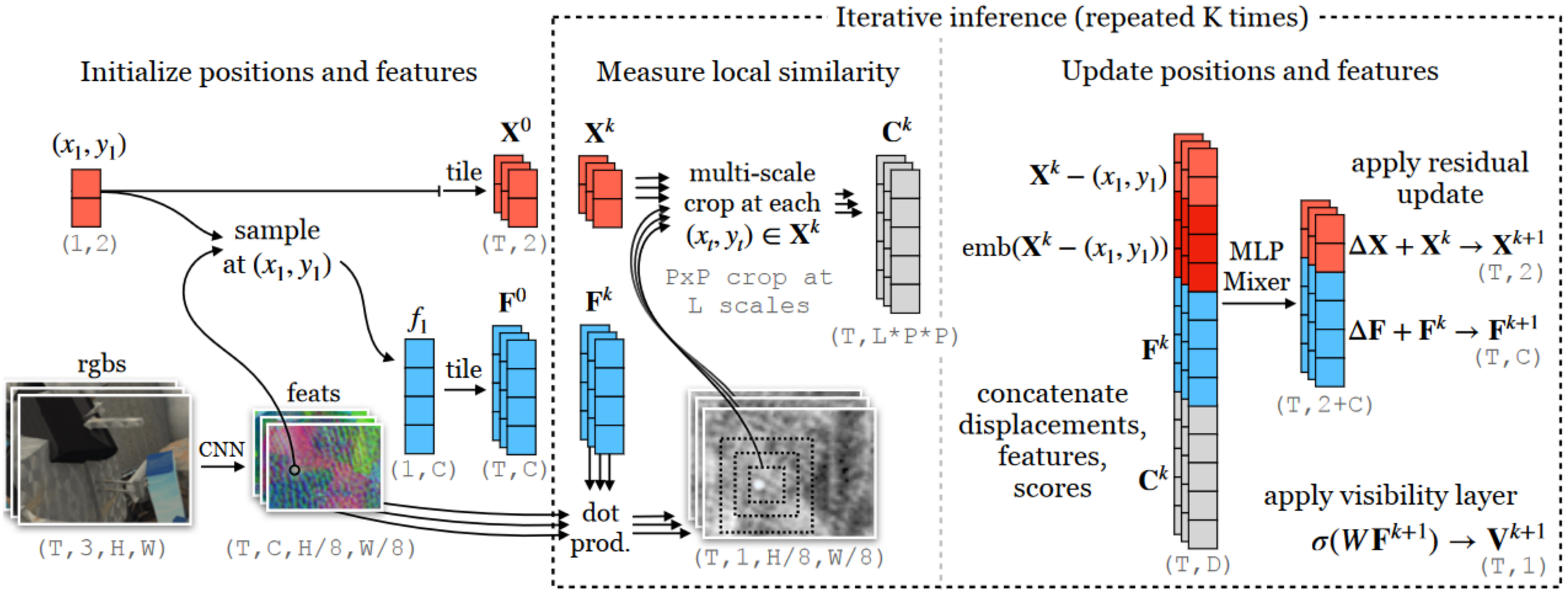
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Particle Video Revisited



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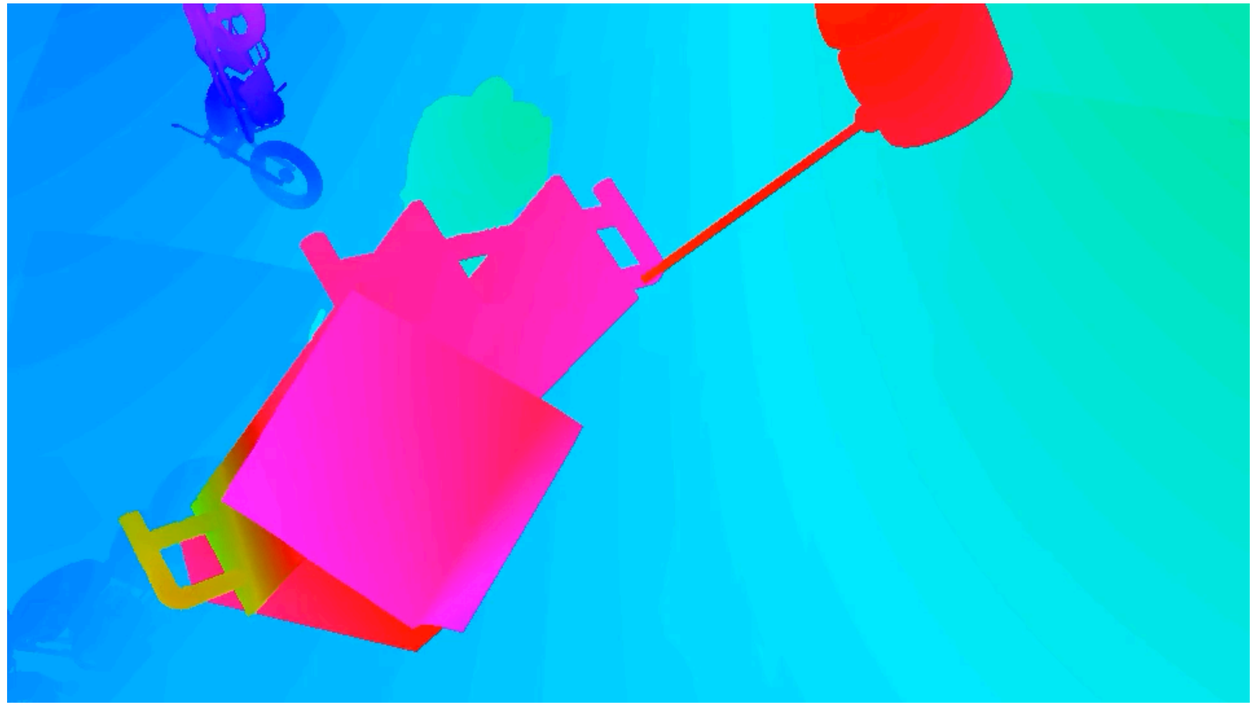
Particle Video Revisited



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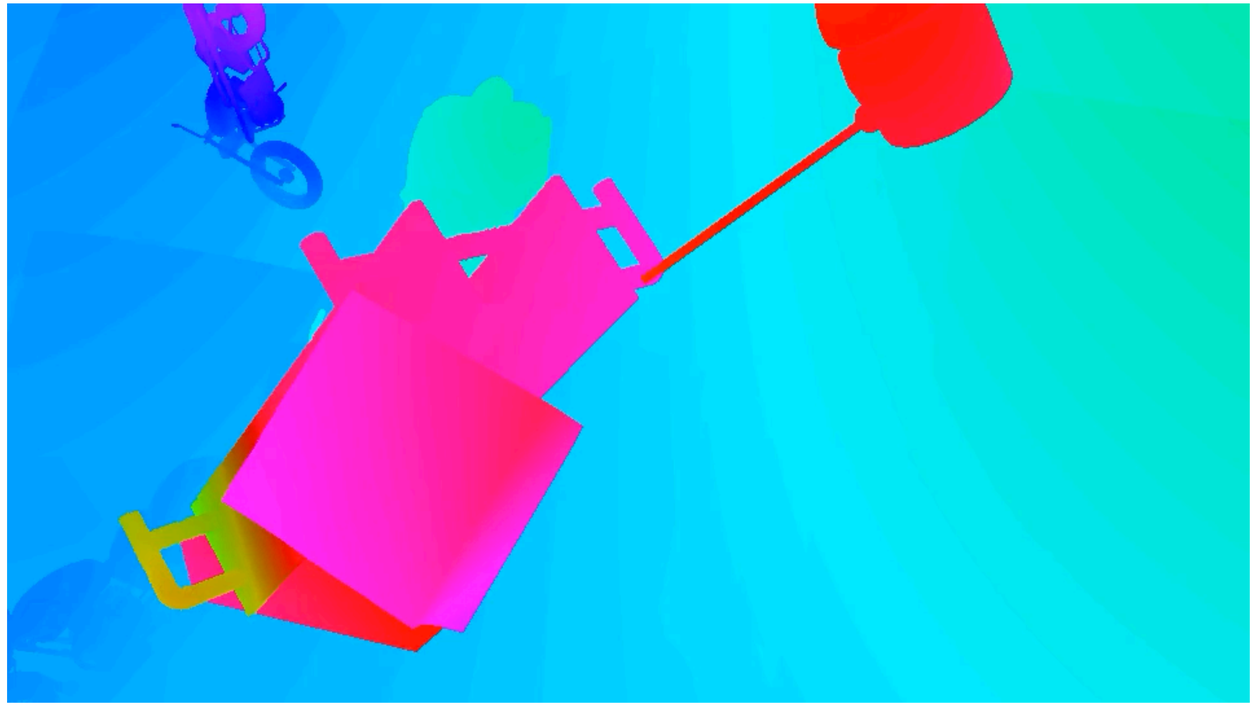
Trained Fully Supervised on Synthetic Data



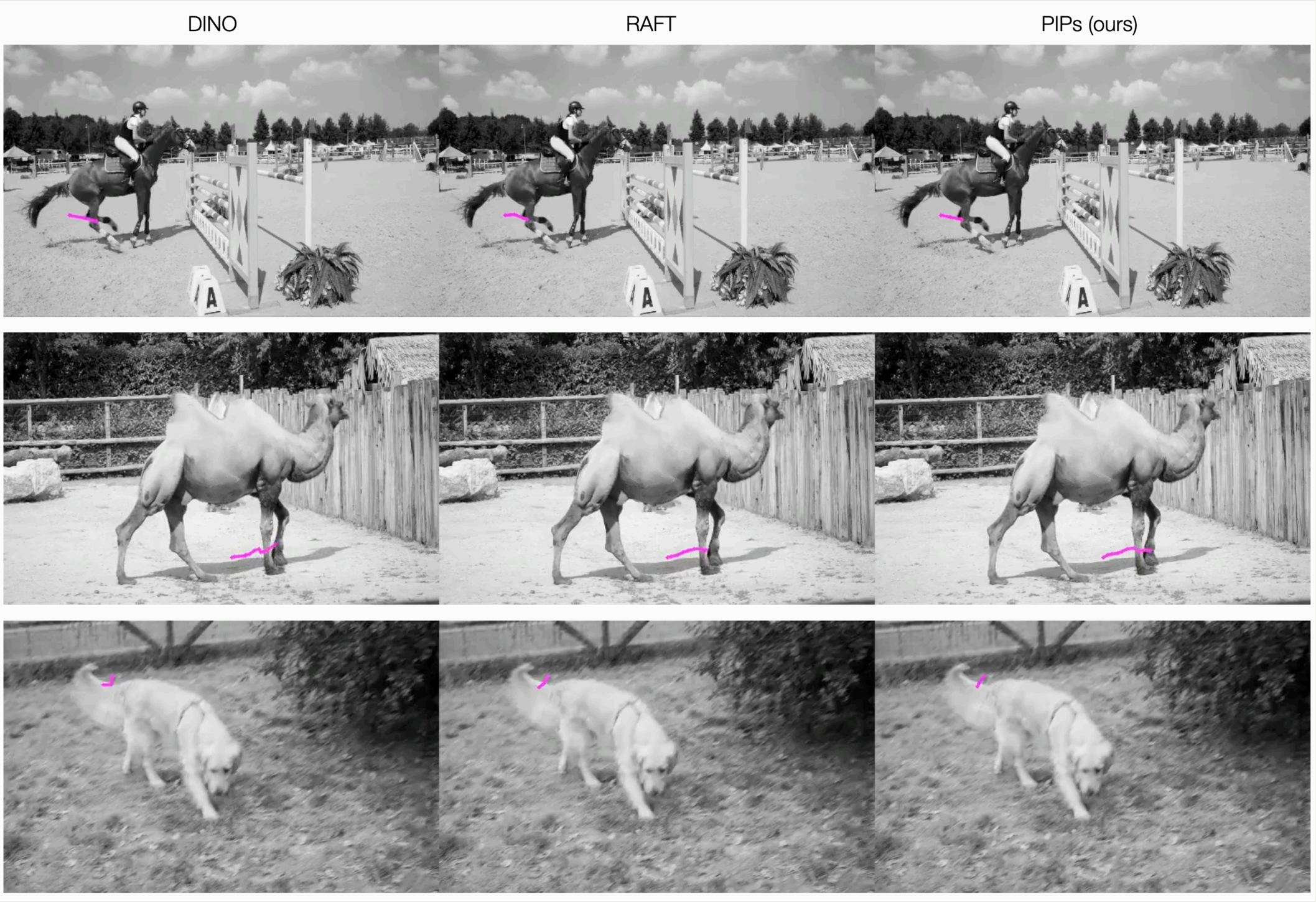


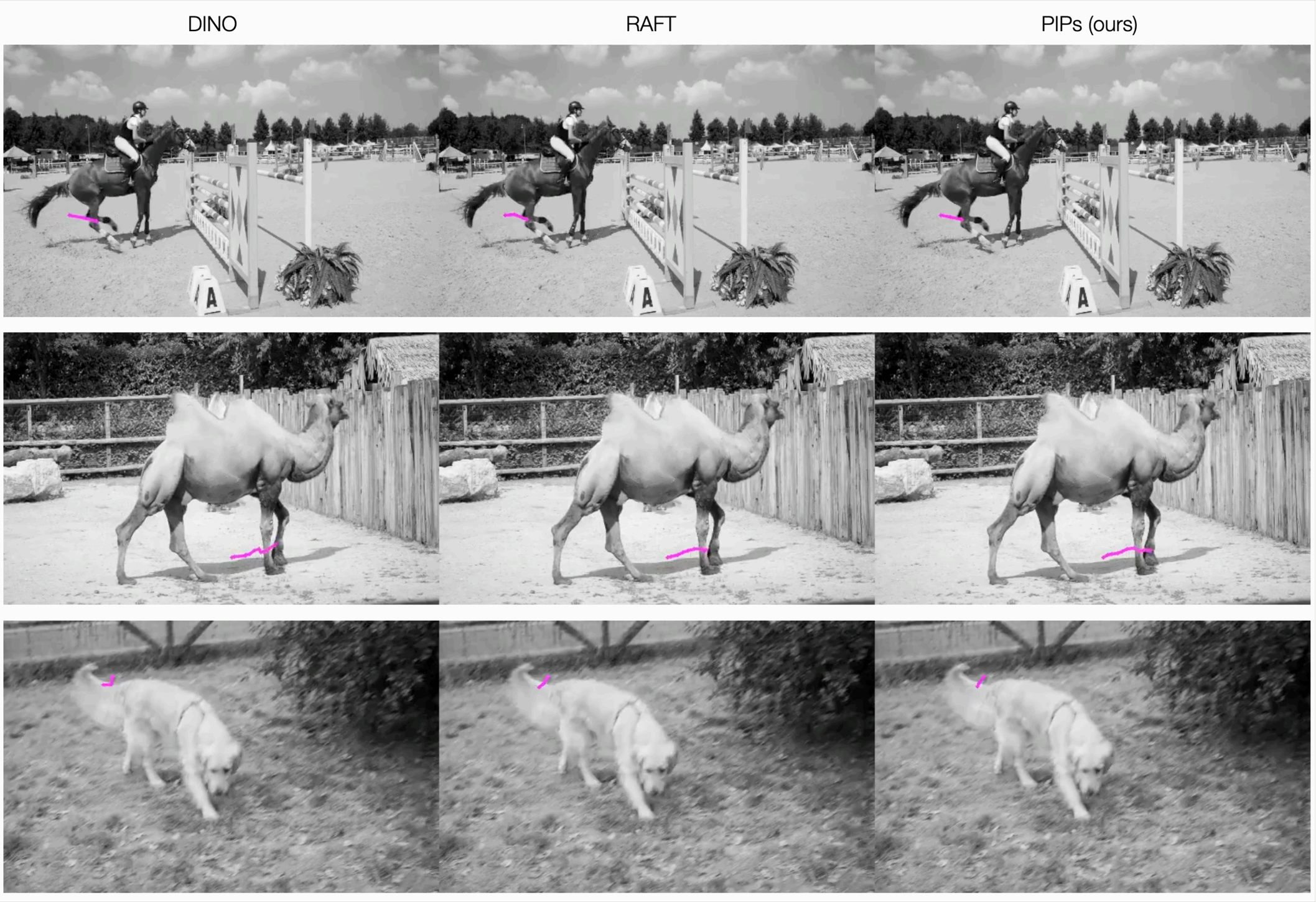
Trained Fully Supervised on Synthetic Data



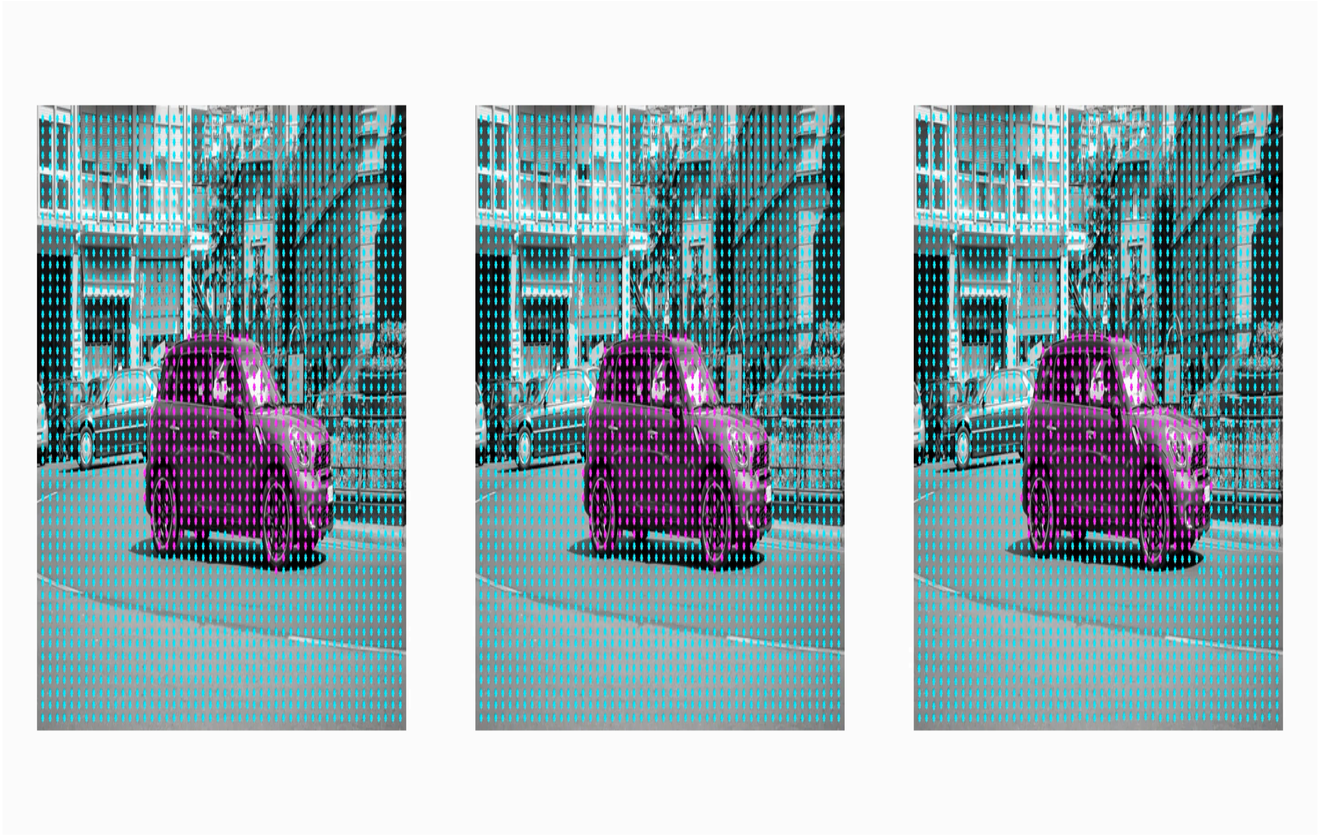


A Large Dataset to Train Convolutional Networks for Disparity, Optical Flow, and Scene Flow Estimation, Mayer et al., 2016


DINO
RAFT
PIPs (ours)

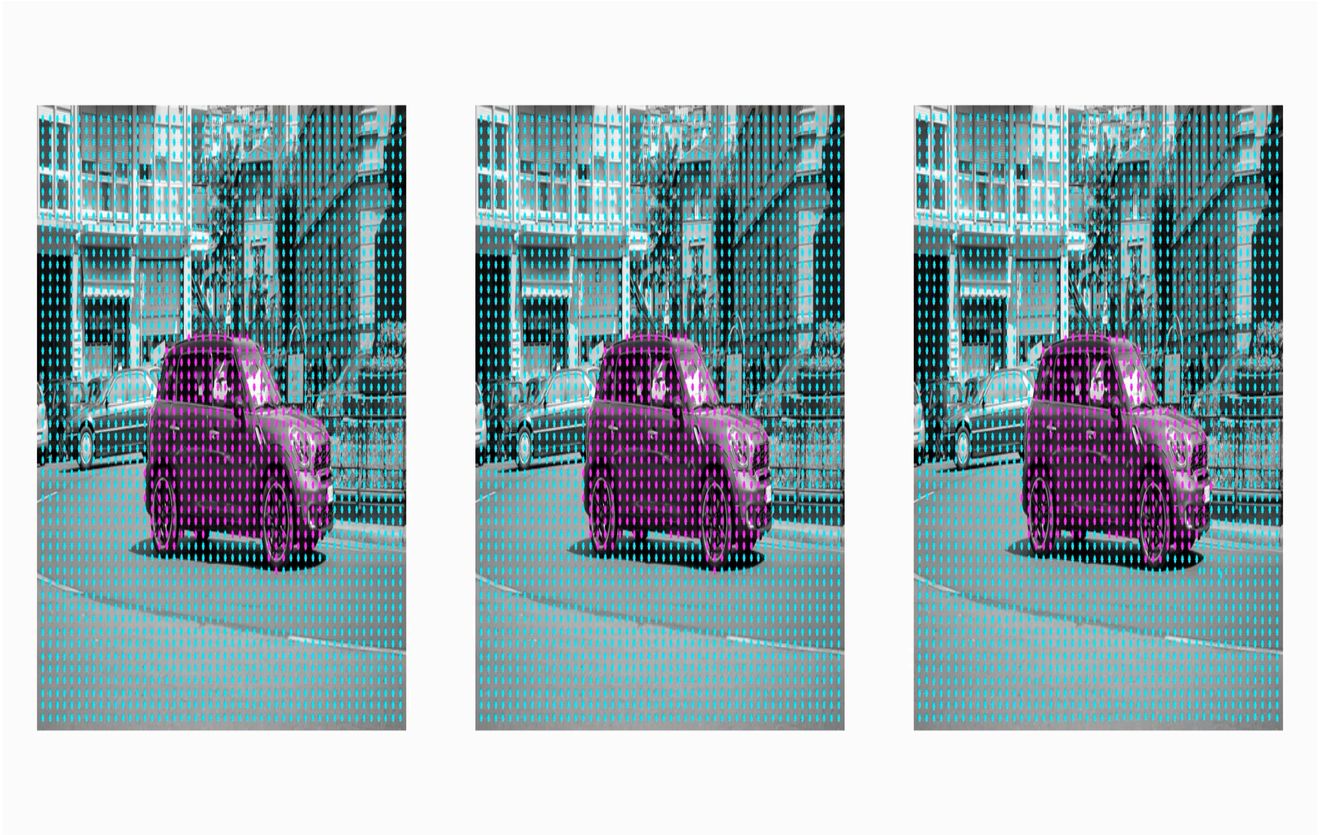

DINO
RAFT
PIPs (ours)

Single Point Tracking



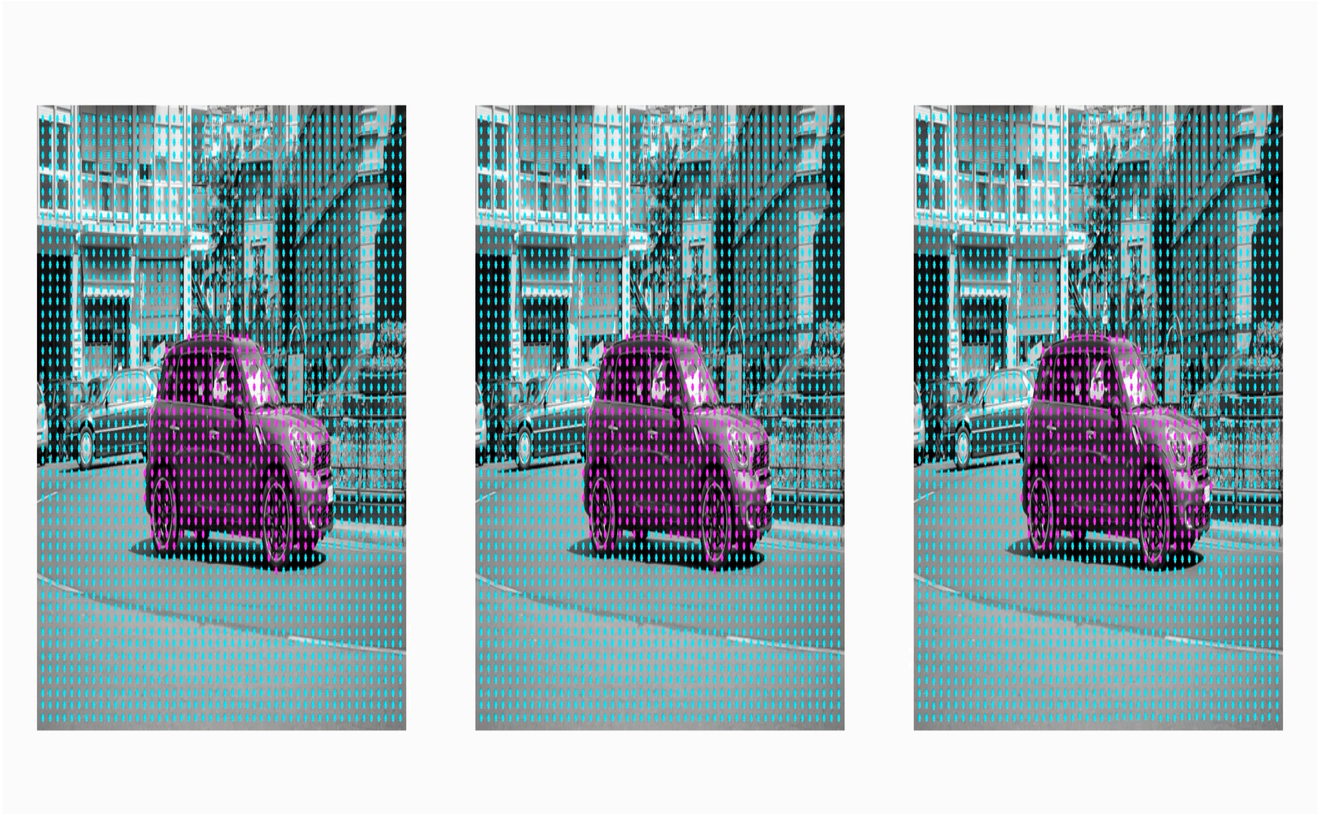
- Background points
- Object points

Single Point Tracking



- Background points
- Object points

Single Point Tracking

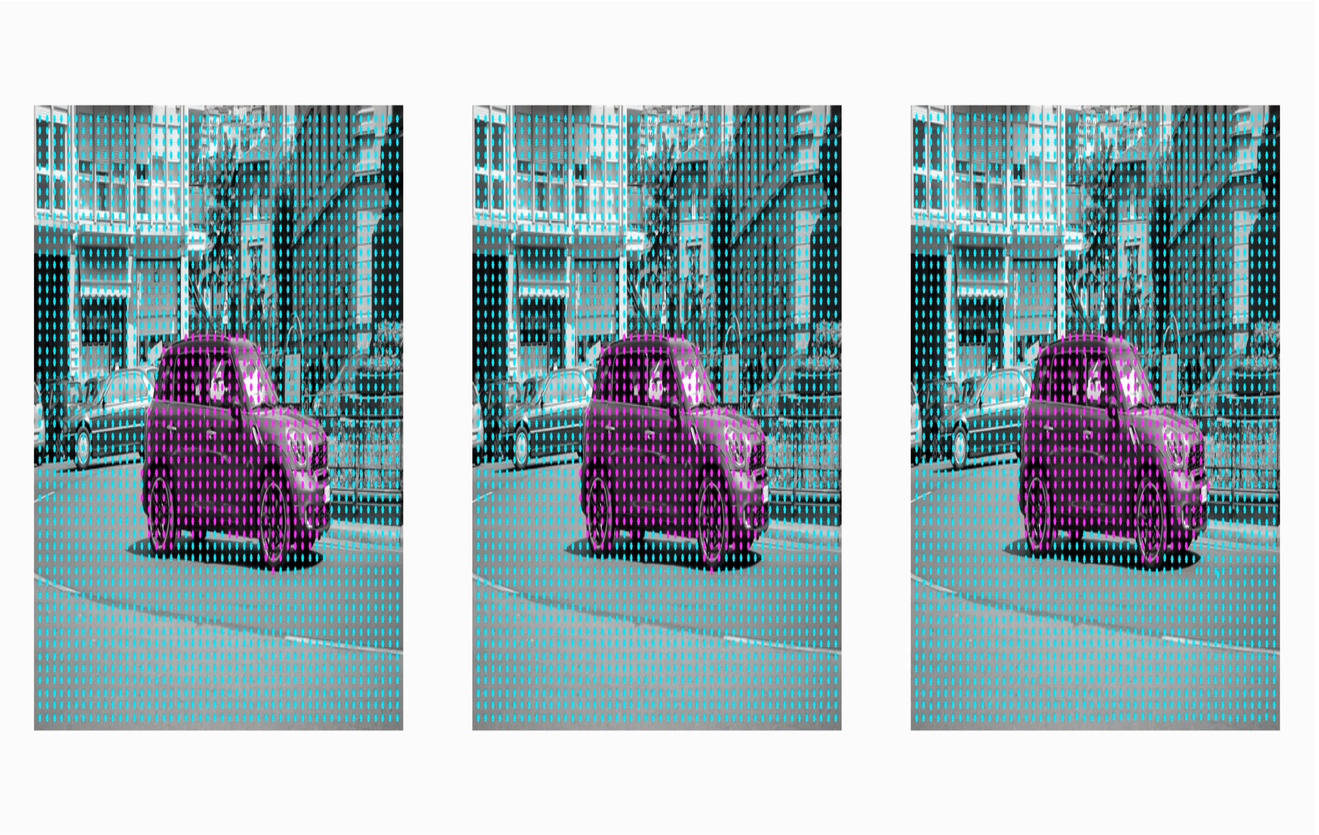


- Background points
- Object points

Tracking single points lacks global consistency

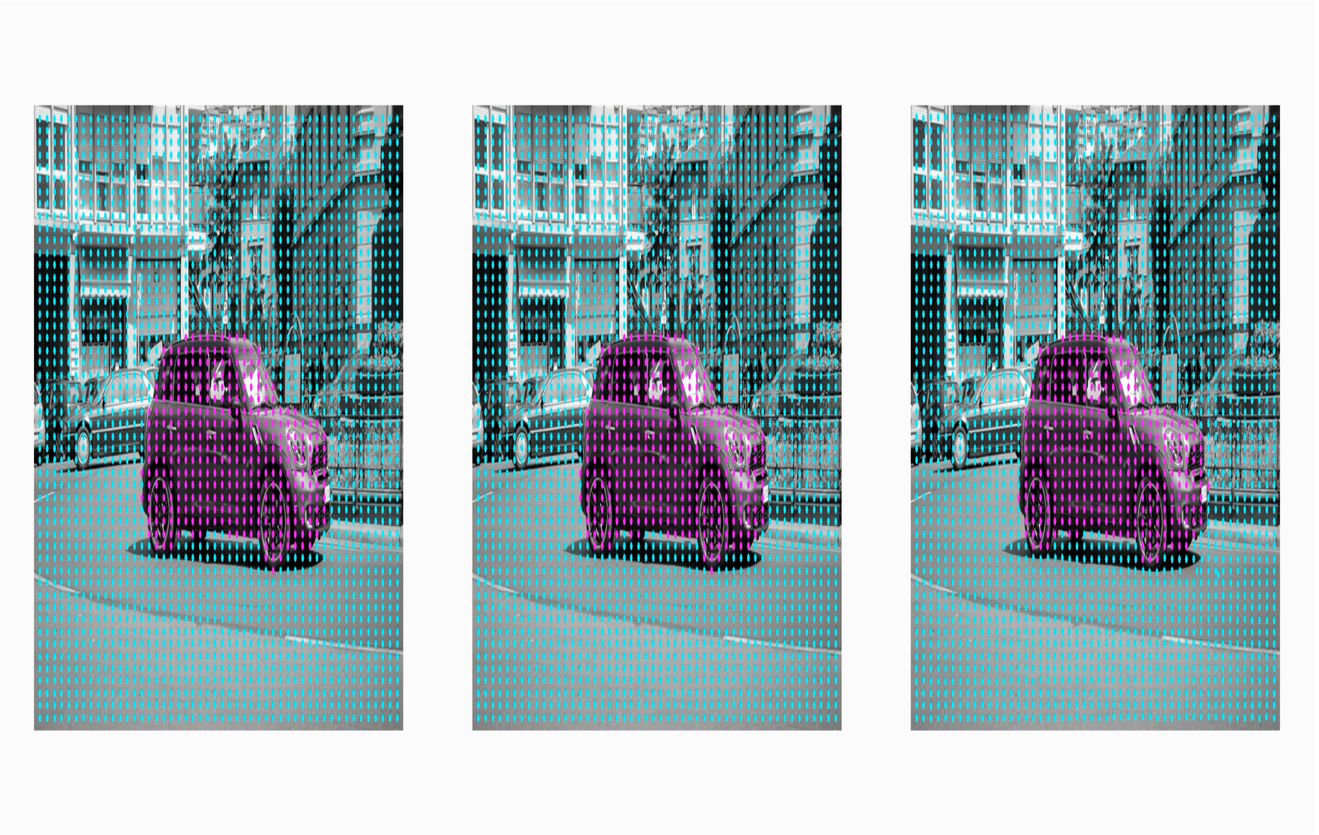
Points drift relative to each other

Tracking with Optical Flow



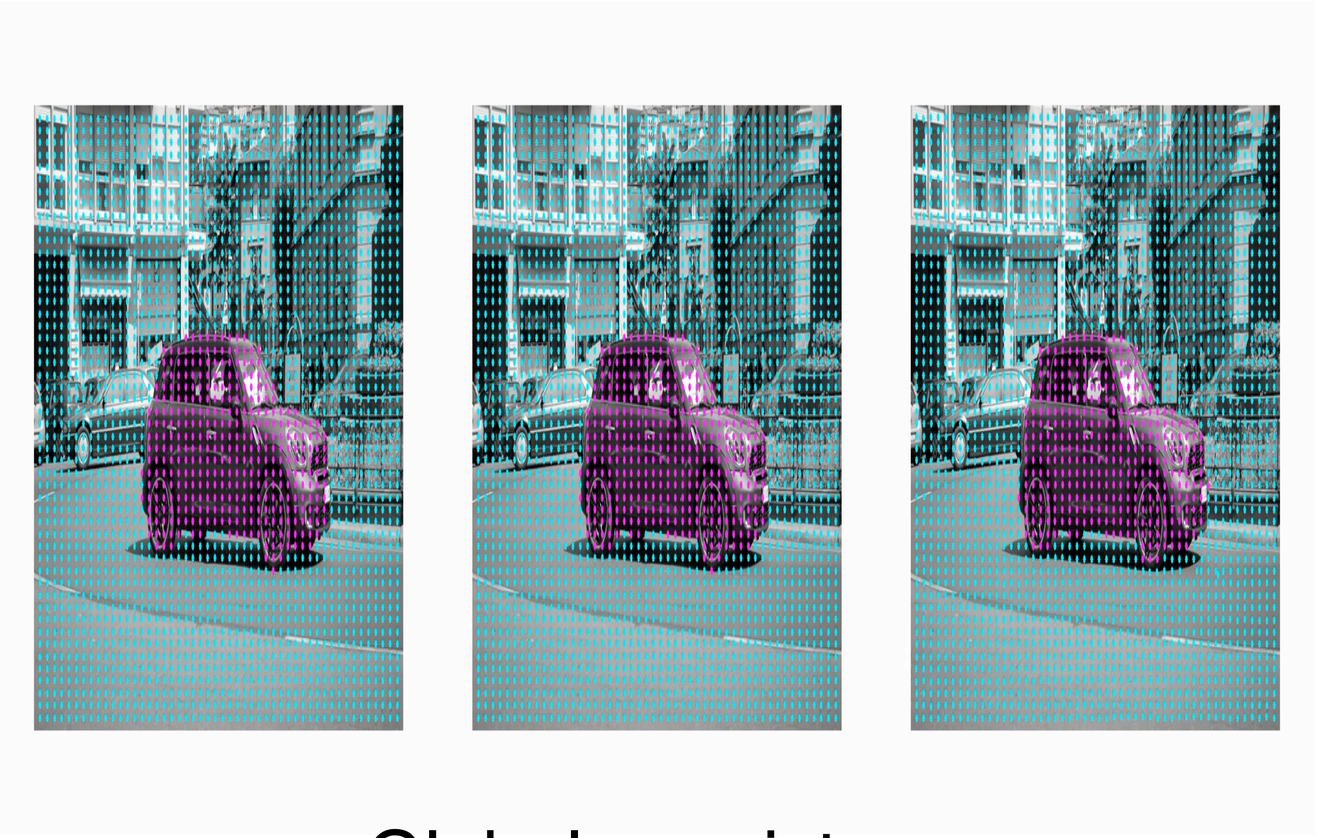
- Background points
- Object points

Tracking with Optical Flow



- Background points
- Object points

Tracking with Optical Flow

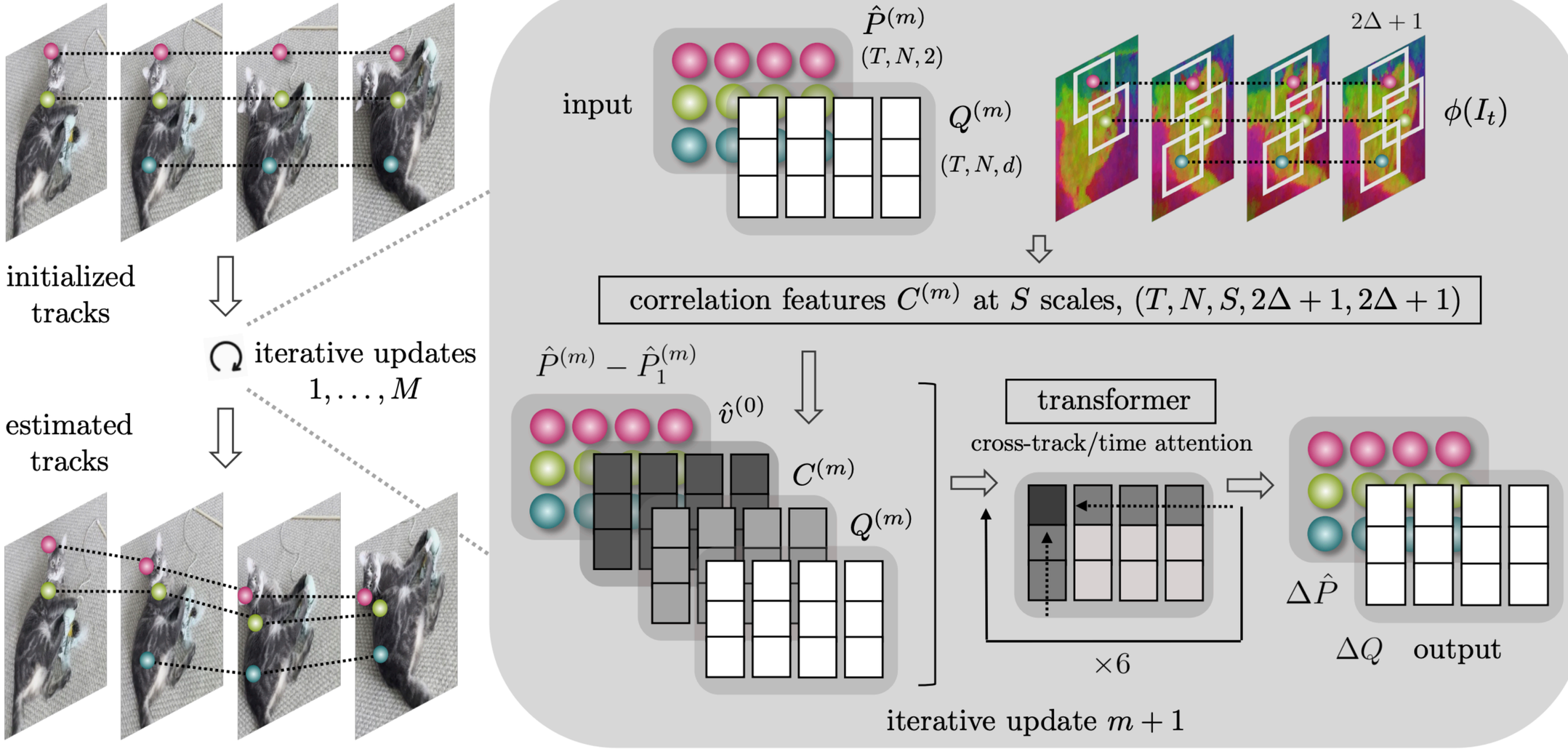


- Background points
- Object points

Global consistency

Occlusion problem: background accumulates on the object

CoTracker: It is Better to Track Together



Tracking Points Together

CoTracker: It is Better to Track Together, N Karaev et al., 2023

Tracking Points Together

- Global consistency from tracking many points

CoTracker: It is Better to Track Together, N Karaev et al., 2023

Tracking Points Together

- Global consistency from tracking many points
- Occlusion handling from long-term tracking

CoTracker: It is Better to Track Together, N Karaev et al., 2023

Tracking Points Together

- Global consistency from tracking many points
- Occlusion handling from long-term tracking
- Train on synthetic data only

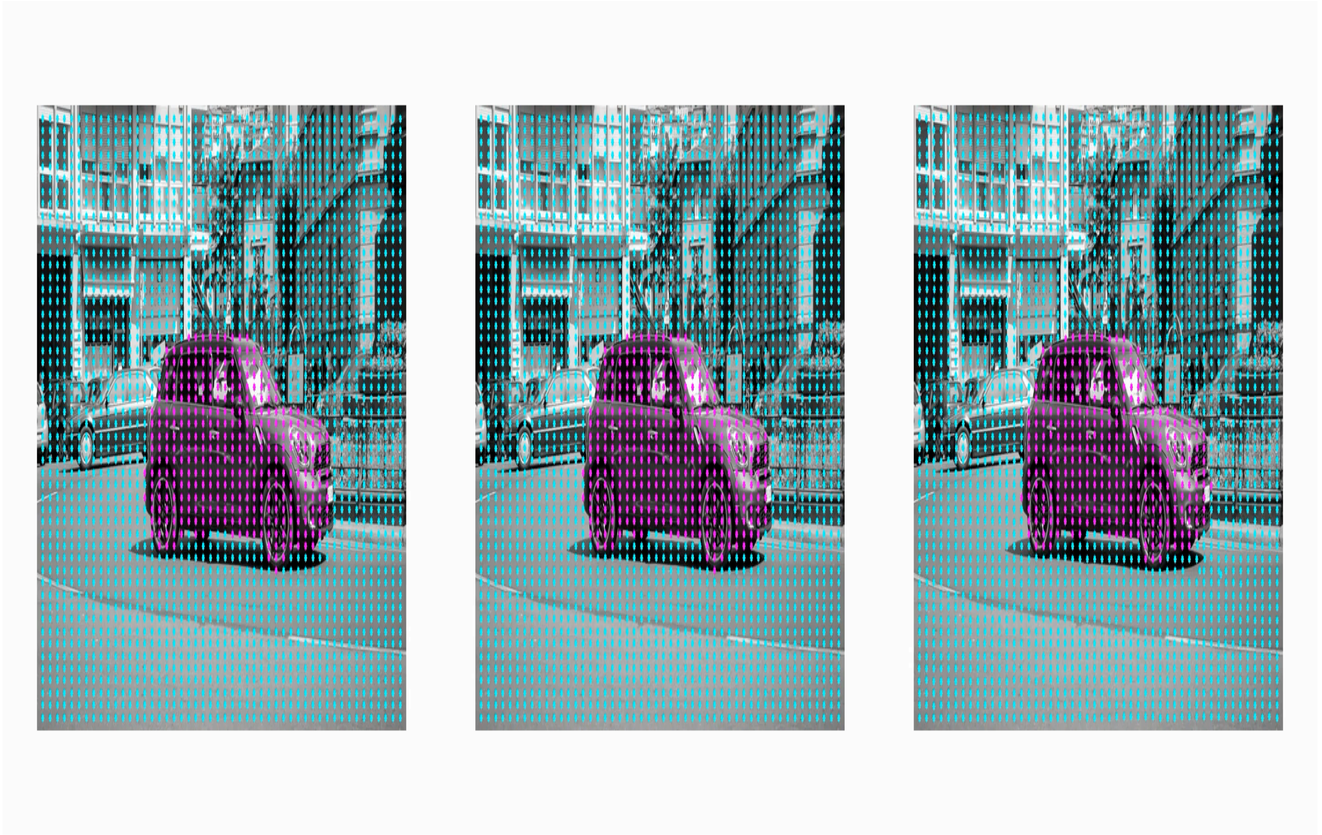
CoTracker: It is Better to Track Together, N Karaev et al., 2023

Tracking Points Together

- Global consistency from tracking many points
- Occlusion handling from long-term tracking
- Train on synthetic data only
- Main mechanism:
  - Transformer architecture
  - Factorised attention: space, time, and group (across tracks)

CoTracker: It is Better to Track Together, N Karaev et al., 2023

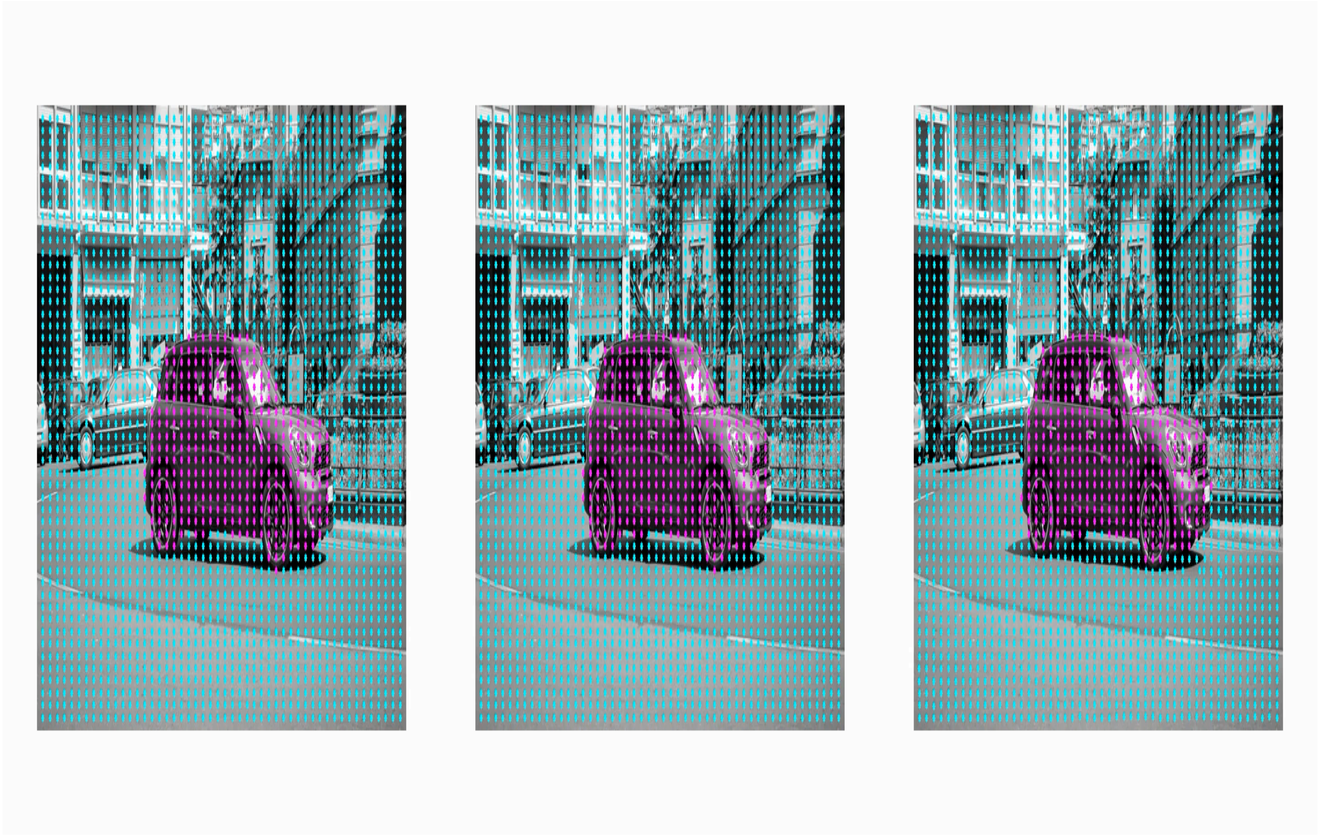
Tracking Points Together



- Background points
- Object points

- Better global consistency
- Better occlusion handling

Tracking Points Together



- Background points
- Object points

- Better global consistency
- Better occlusion handling

Tracking Points Together



Tracking Points Together



Tracking Points Together



Tracking Points Together



Summary

- Discussed two key approaches to motion tracking: Optical flow and point tracking
- Went in-depth on how to think about the motion estimation problem: infinitesimal perspective, finite perspective, cost volumes, smoothness, etc.
- Discussed SOTA supervised optical flow estimators.
- Discussed options for self-supervised methods.
- Discussed point tracking paradigm.