CS4243
Computer Vision & Pattern Recognition

AY 2023/24

Lab Session 6

NUS National University of Singapore | School of Computing

Arrangement

- Part 1 – Quick Recap from the Lecture (~10 min)
- Part 2 – Lab Tutorial (~40 min)
- Break (10 min)
- Part 3 – Lab Solution (~20 min)

Lab Materials

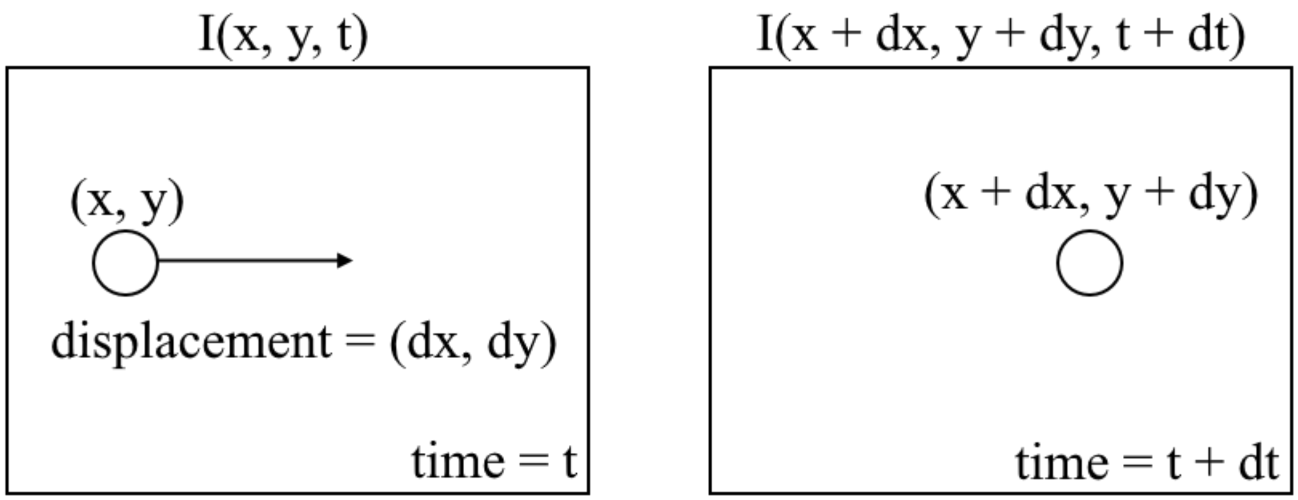
- GitHub Repo: https://github.com/ldkong1205/cs4243_lab
- Slides
- Notebook & Solution
- Other Materials (image, media, etc.)

Lesson 5

Motion Detection and Optical Flow

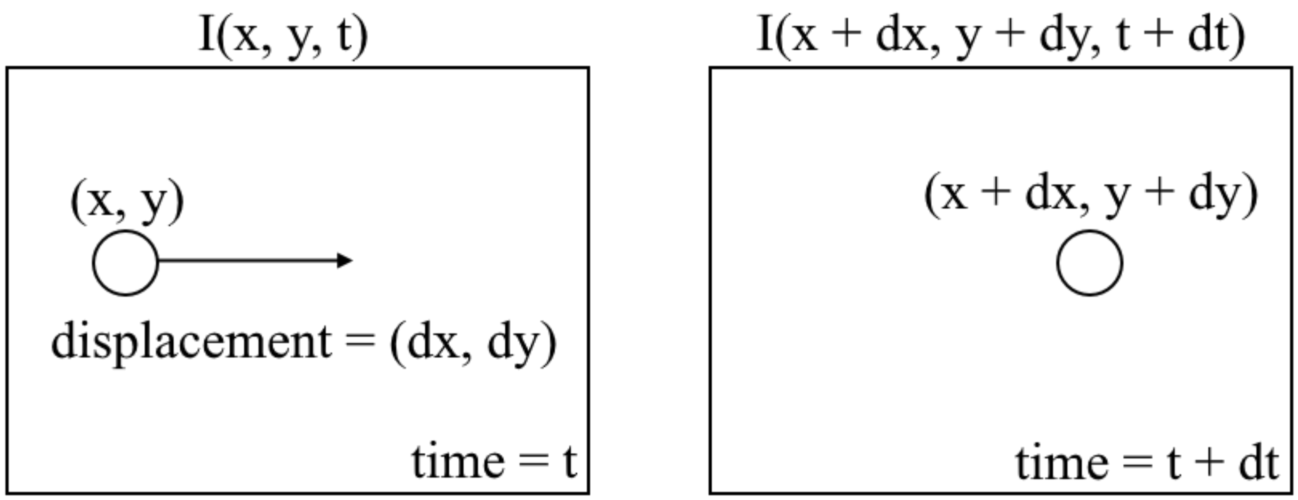
Optical Flow

Optical flow is the motion of objects between consecutive frames of sequence, caused by the relative movement between the object and camera. The problem of optical flow may be expressed as:



Optical Flow

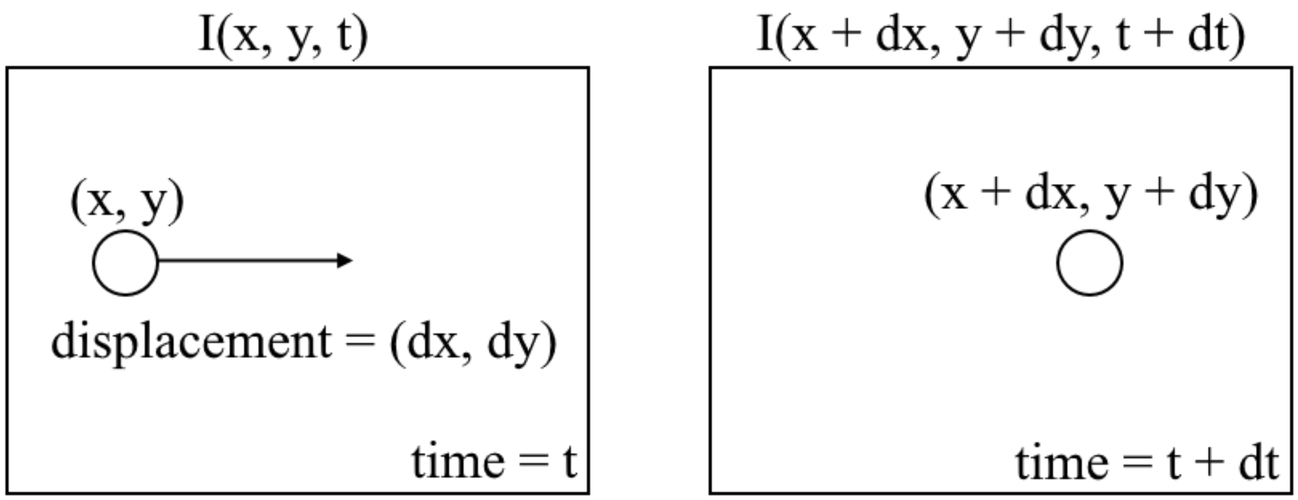
where between consecutive frames, we can express the image intensity, I, as a function of space (x, y) and time (t).



Optical Flow

In other words, if we take the first image $I(x, y, t)$ and move its pixels by (dx, dy) over t time, we obtain the new image:

$$I(x + dx, y + dy, t + dt)$$



Optical Flow

First, we assume that pixel intensities of an object are constant between consecutive frames:

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

Optical Flow

First, we assume that pixel intensities of an object are constant between consecutive frames:

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

Second, we take the Taylor Series Approximation of the RHS and remove common terms:

$$I(x + \delta x, y + \delta y, t + \delta t) = I(x, y, t) + \frac{\partial I}{\partial x}\delta x + \frac{\partial I}{\partial y}\delta y + \frac{\partial I}{\partial t}\delta t + \ldots$$

$$\Rightarrow \frac{\partial I}{\partial x}\delta x + \frac{\partial I}{\partial y}\delta y + \frac{\partial I}{\partial t}\delta t = 0$$

Optical Flow

Third, we divide by dt to derive the optical flow equation:

$$\frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v + \frac{\partial I}{\partial t} = 0$$

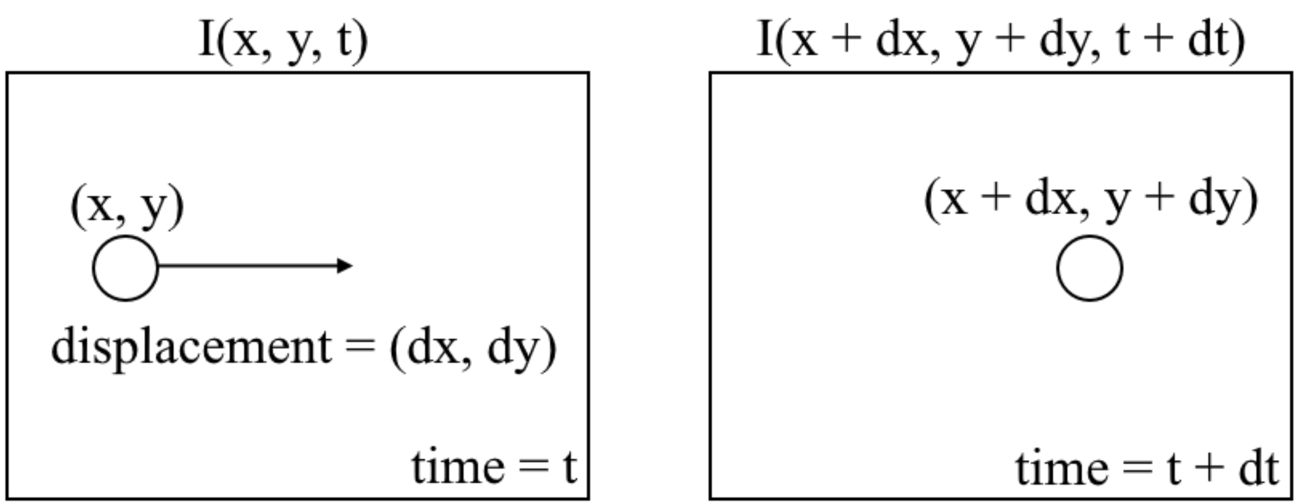
where u = dx/dt and v = dy/dt.

dI/dx, dI/dy, and dI/dt are the image gradients along the horizontal axis, the vertical axis, and time.

Optical Flow

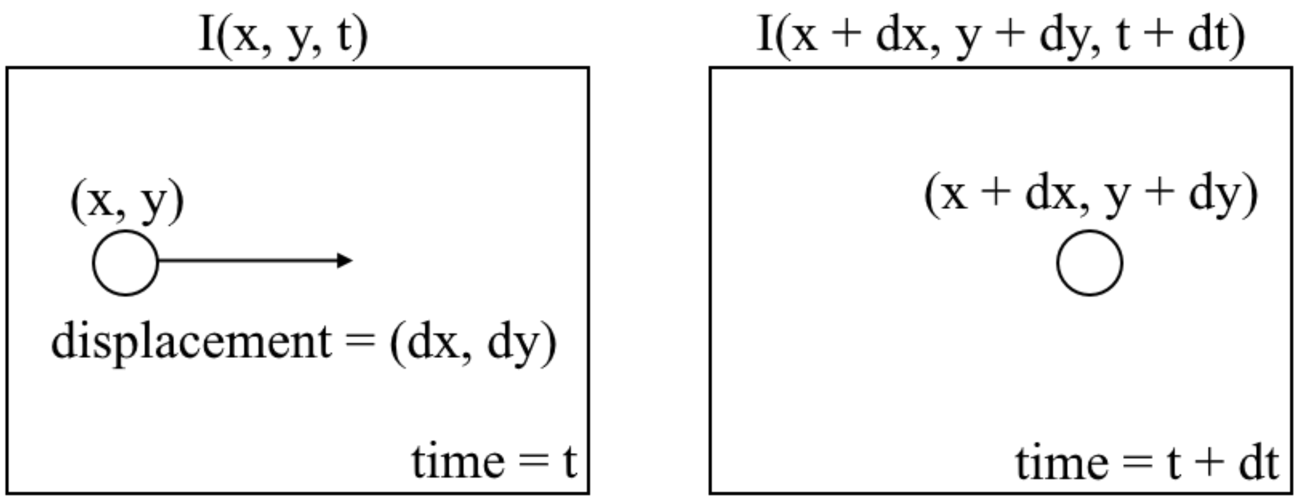
Summary:

Optical flow -> Solving u(dx/dt) and v(dy/dt) to determine movement over time.



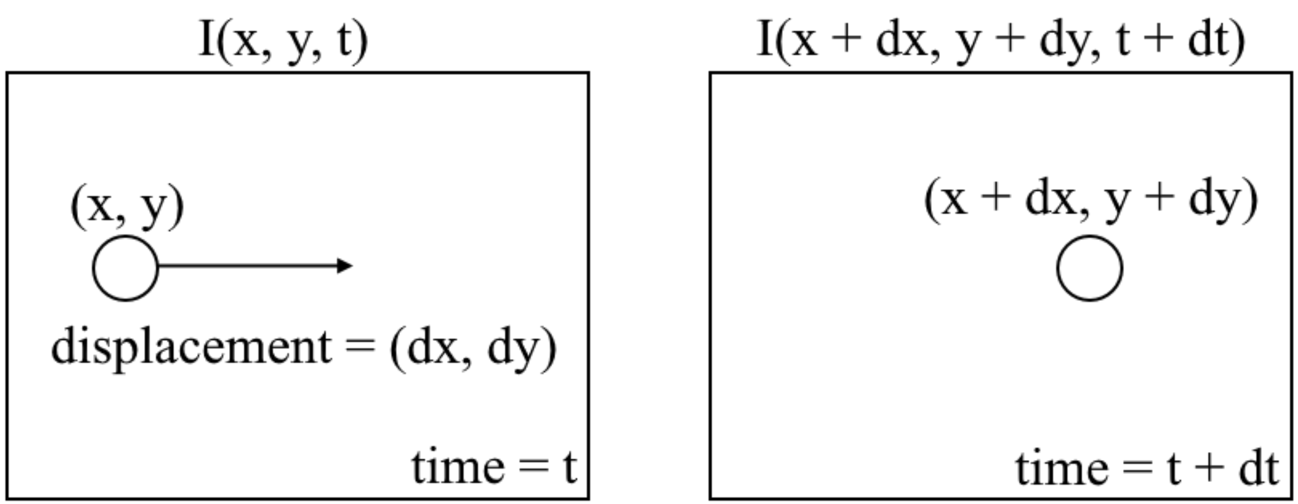
Optical Flow

You may notice that we cannot directly solve the optical flow equation for u and v, since there is only one equation for two unknown variables.



Optical Flow

In today's lab, we will implement some methods such as the Lucas-Kanade method to address this issue.



Sparse *vs.* Dense Optical Flow

Left: Sparse Optical Flow – track a few "feature" pixels.

Right: Dense Optical Flow – estimate the flow of all pixels in the image.

Tracking Specific Objects

There might be scenarios where you want to only track a specific object of interest, or one category of objects.

Lucas-Kanade: Sparse Optical Flow

Lucas and Kanade proposed an effective technique to estimate the motion of interesting features by comparing two consecutive frames in their paper

"An Iterative Image Registration Technique with an Application to Stereo Vision," IJCAI, 1981.

Lucas-Kanade: Sparse Optical Flow

The Lucas-Kanade method works under the following assumptions:

1. Two consecutive frames are separated by a small time increment (dt) such that objects are not displaced significantly (in other words, the method work best with slow-moving objects).

2. A frame portrays a "natural" scene with textured objects exhibiting shades of gray that change smoothly.

Lucas-Kanade: Sparse Optical Flow

Sparse optical flow of horses on a beach.

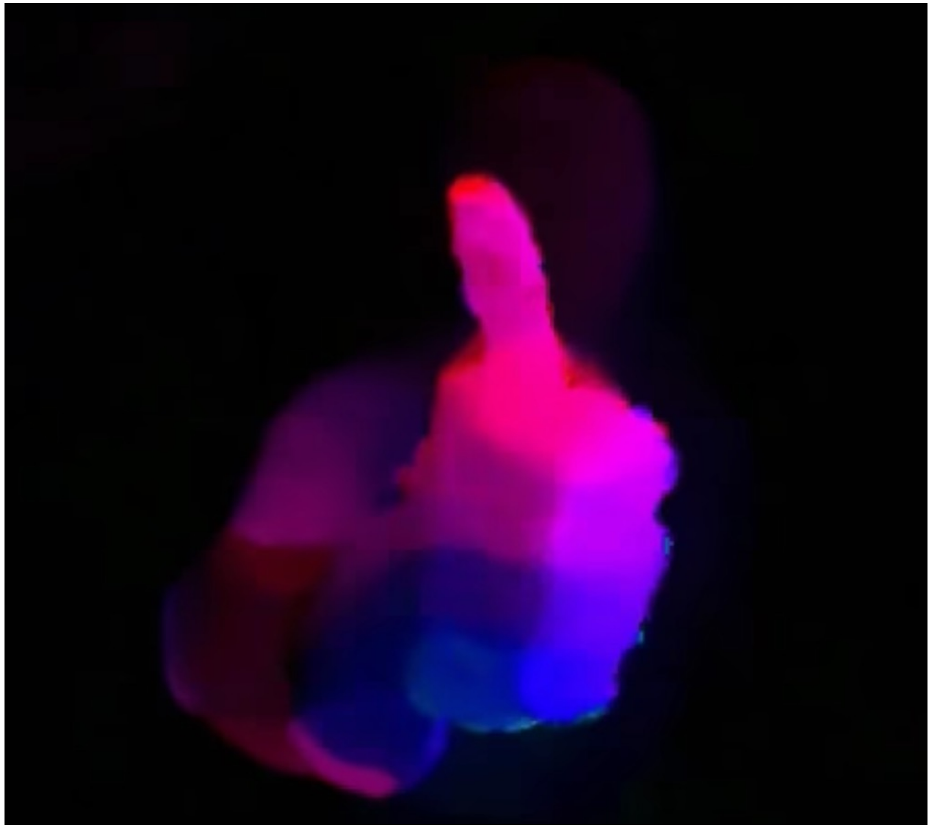
Optical Flow using Deep Learning

While the problem of optical flow has historically been an optimization problem, recent approaches by applying deep learning have shown impressive results.

Generally, such approaches take two video frames as input to output the optical flow (color-coded image), which may be expressed as:

$$(u, v) = f(I_{t-1}, I_t)$$

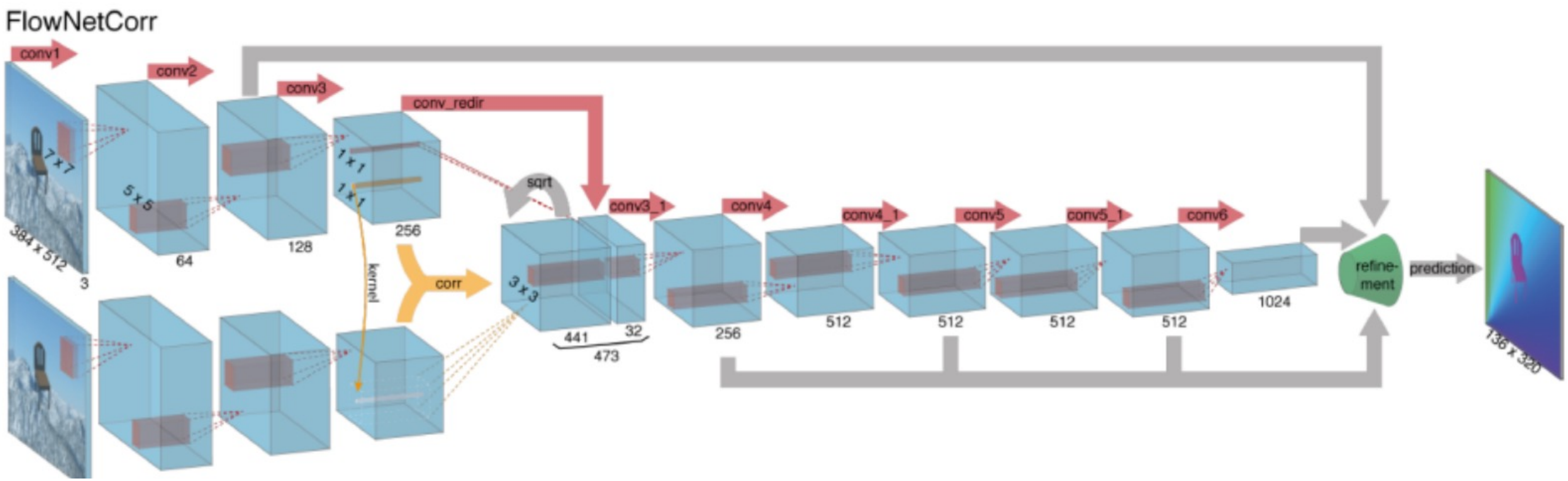
Optical Flow using Deep Learning



Output of a deep learning model: color-coded image.

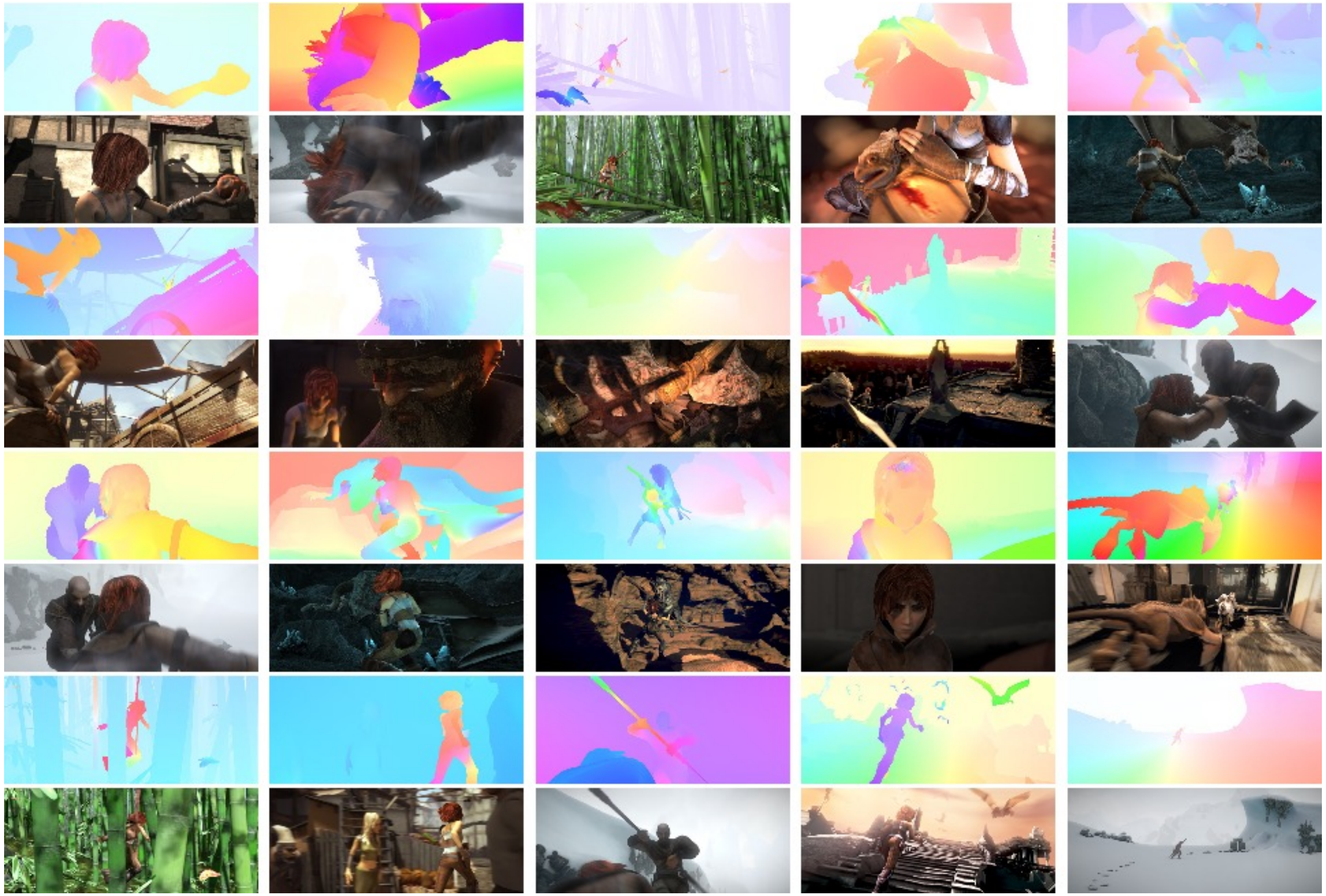
Color encodes the direction of pixel while intensity indicates their speed.

Optical Flow using Deep Learning



Architecture of FlowNetCorr, a convolutional neural network for end-to-end learning of optical flow.

Optical Flow using Deep Learning



Synthetically generated data for training Optical Flow Models – the MPI-Sintel dataset.

Optical Flow using Deep Learning

Synthetically generated data for training Optical Flow Models – the Flying Chairs dataset.

Application: Semantic Segmentation

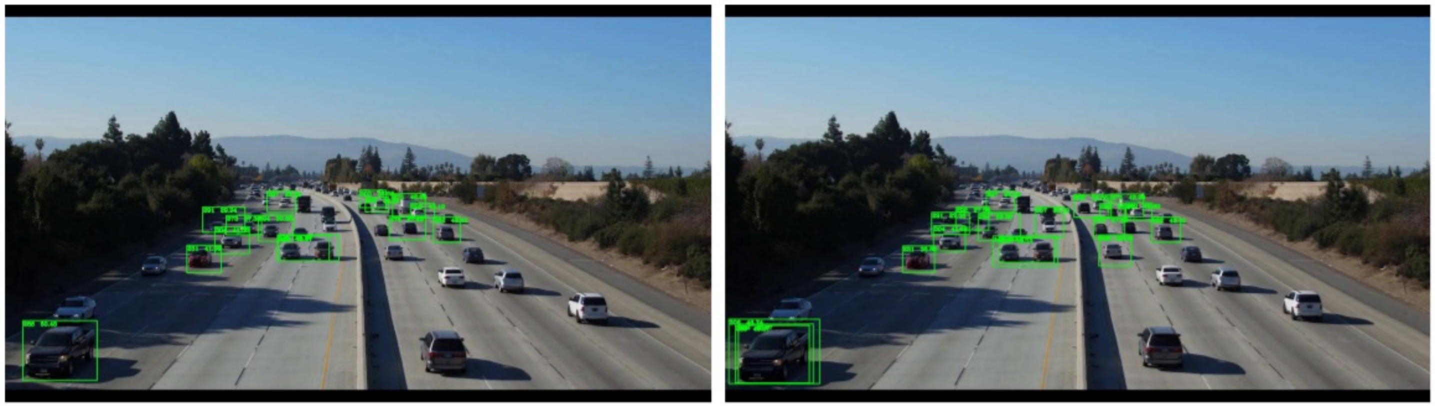
Original Slice	Groundtruth	Optical Flow	3D OF UCM

Semantic segmentation generated from optical flow.

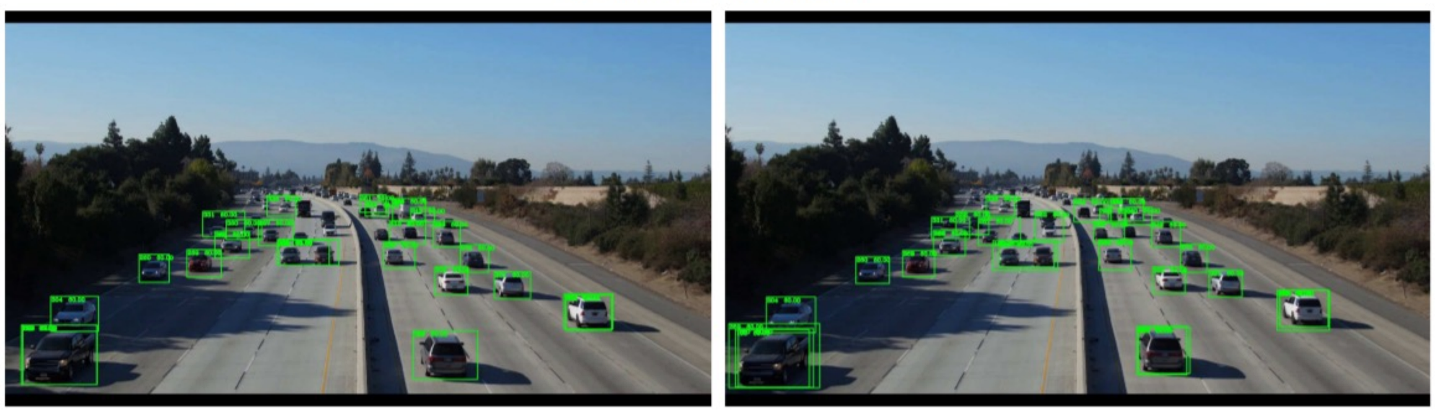
Application: Object Detection & Tracking

Real-time tracking of vehicles with optical flow.

Application: Object Detection & Tracking



(a) Predicted Speed Model



(b) Constant Speed Model

Optical flow can be used to predict vehicle speeds.

Lab Session 6

Optical Flow

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