Video Analysis

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Optical Flow Estimation

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Acknowledgement

These slides were developed by Nicole Brosch in previous years. We wish to thank Nicole for making the slides available for further use.

Overview

- **Basics**
  - Motion Field, Applications, Key Problems, Motion Estimation Techniques
- **Matching**
  - Block Matching, Brightness Constancy, 2D Motion vs. Optical Flow
- **Gradient-based approaches**
  - Optical Flow Equation, Aperture Problem, Lucas-Kanade, Horn-Schunck
- **Challenges**
  - Large Motion, Illumination Changes, ...
- **Evaluation**
  - Ground Truth, Middlebury Data Set

Basics

- **Goal of Optical Flow Estimation**

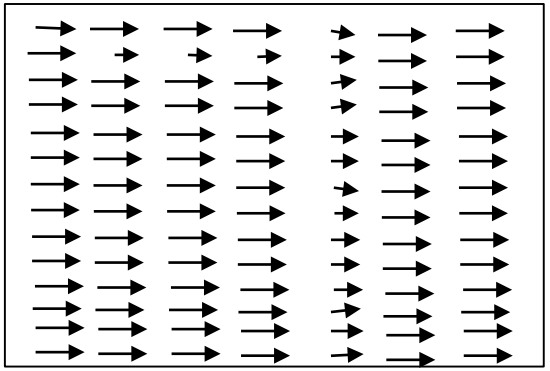
  The goal of OF estimation is to compute an approximation of the *motion field* (optical flow field) from a video sequence.

- **Motion Field**

  A vector field, which vectors indicate *direction* (orientation) and *velocity* (length) of movement.

Frame 1

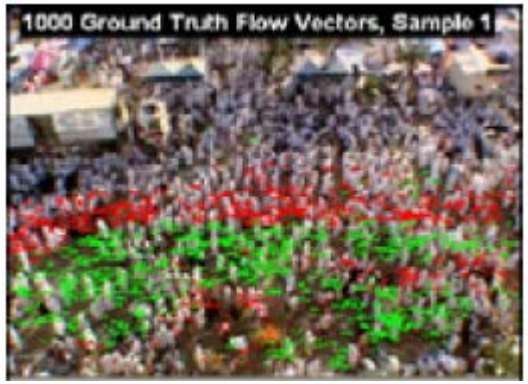
Frame 2



Motion Field

Applications

- **Why estimate visual motion?**
  - Motion detection (e.g., surveillance)
  - Video understanding (e.g., video segmentation)
  - Compositing (e.g., retiming)
  - Interactive 2D-to-3D conversion
  - Video compression (e.g., MPEG)
  - Obstacle avoidance
  - Image registration
  - …



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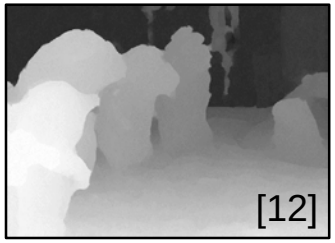
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Key Problems

- **Motion representation**
  - E.g. Pixel, sub-pixel
  - E.g. Regions, blocks, segments, …
- **Choose motion estimation criteria & formulate it as function**
  - E.g. Intensities / colors are conserved
  - E.g. Intensity / color changes are conserved
  - E.g. Smooth vector fields
- **Minimize function with an optimization method**
  - Exhaustive search / continuous / discrete / variational
  - Depends on function

Motion estimation techniques

- **Block- / Feature- Matching**

  simply *searches* for the block/patch/feature which fits best.

- **Gradient-based methods**

  formulates equation(s) and *solves* for the estimates.

- **Variational Methods**
- **Spatiotemporal Methods**
- **Segmentation-based Methods**
- **Probabilistic Methods**
- **Learning-based Methods**
- **...**

Block- / Feature-Matching

Block Matching

- **Representation:** Blocks centred at a pixel
- **Constraint**: Intensities are shifted -> values are conserved
- **Optimization:** Exhaustive search of block with minimal difference

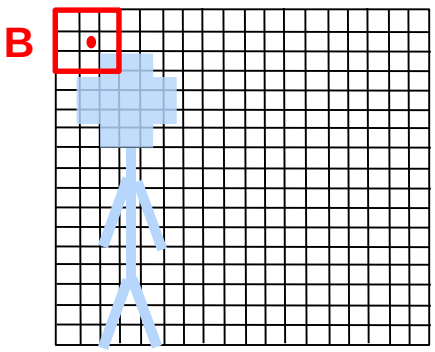
Brightness Constancy Assumption

costs, which should be minimized

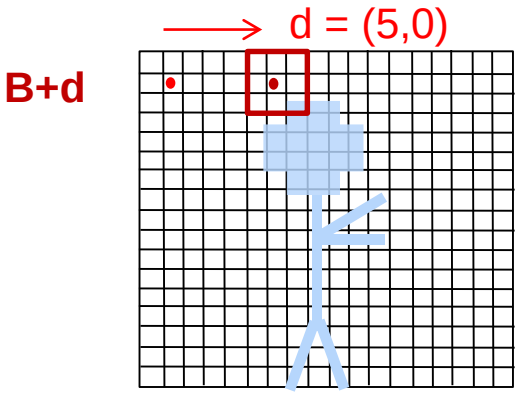
$$E(d) = \sum_{p \in B} c(p, p+d)$$

c(.) .... Similarity measure e.g., squared differences

d ... OF vector
B .. block
p .. pixel



Frame 0



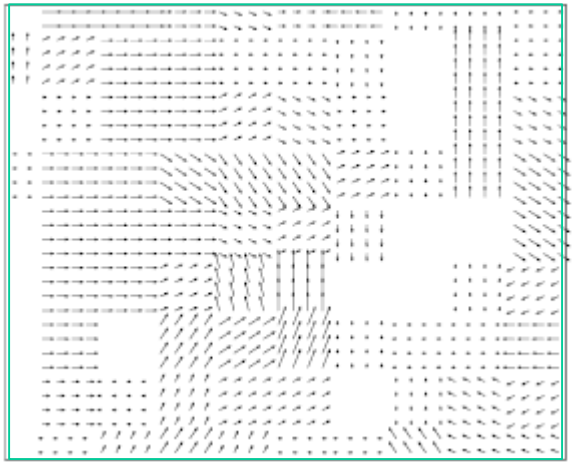
Frame 1

Block Matching

- **Advantages:**
  - Easy :)

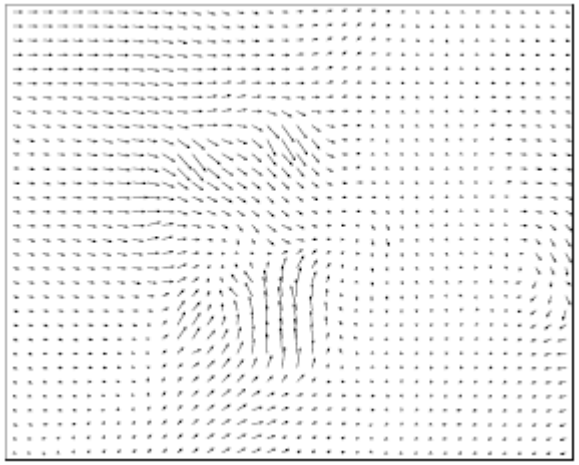
- **Disadvantages:**
  - Block artifacts
  - Edges inside a block are smoothed
  - Not accurate
  - Not efficient (define search windows, ...)
  - Dependent of block size
  - Problems caused by the brightness constancy assumption.

Block Matching



VS.

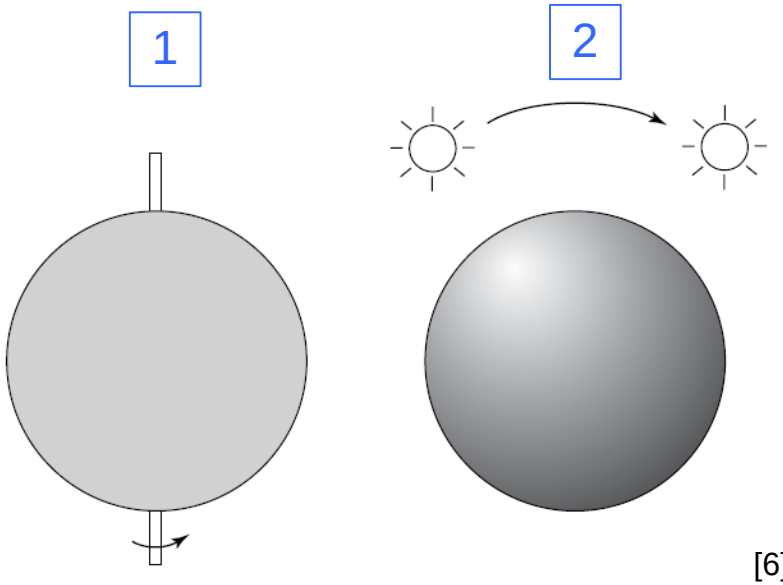
Gradient-based



Consequences of Brightness Constancy

- **2D motion** is the projection of 3D motion. It depends on 3D object motion and projection operator.

- **Optical Flow** is the pattern of *apparent motion* of objects, surfaces and edges in a visual scene caused by the relative motion between a camera and the scene. It depends on illumination and object surface texture.



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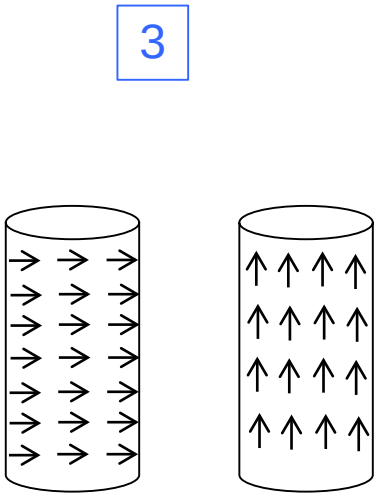
Barber‘s pole



motion field

optical flow

Gradient-Based Approaches

Optical Flow Equation (OFE)

Brightness (Color) Constancy: Pixel intensities (colors) don't change!

I … intensity
(x,y) … pixel
(u,v) .. flow vector
t … time

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

***u* and *v* are small, *I* is smooth -> linearize with Taylor expansion:**

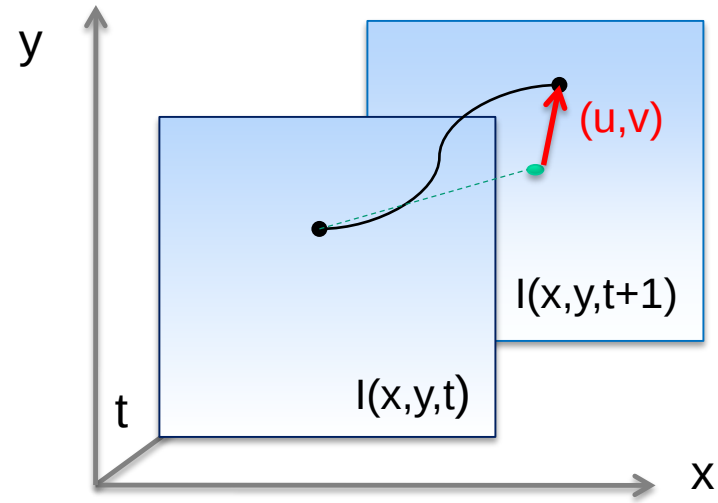
$$I(x+u, y+v, t+1) = I(x,y,t) + uI'_x(x,y,t) + vI'_y(x,y,t) + I'_t(x,y,t)$$

$$\cancel{I(x,y,t)} = \cancel{I(x,y,t)} + uI'_x(x,y,t) + vI'_y(x,y,t) + I'_t(x,y,t)$$

$$0 = uI'_x(x,y,t) + vI'_y(x,y,t) + I'_t(x,y,t)$$

gradient constraint equation

(a.k.a. brightness constancy constraint equation)
(a.k.a. image brightness constancy equation)
(a.k.a. intensity flow equation)

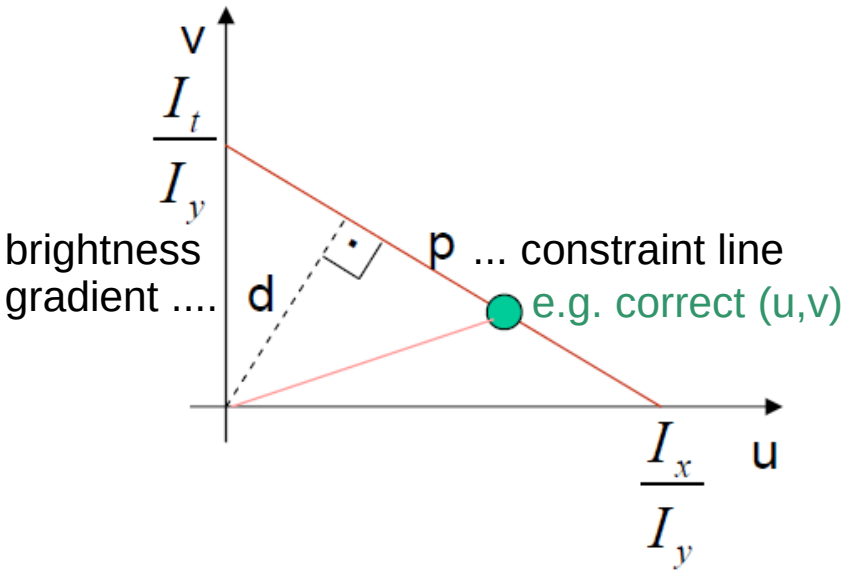


Aperture Problem

- For each pixel *(x,y)* we have one equation with two unknowns *d=(u,v).*

$$0 = uI'_x + vI'_y + I'_t$$

$$-v = u\frac{I'_x}{I'_y} + \frac{I'_t}{I'_y}$$



Correct solution lies on the constraint line p

- Regions with constant brightness -> flow is *indeterminate*!
- **To solve both unknowns we need additional constrains or have to include the neighbourhood!**

Lucas-Kanade

- **Basic Idea:** Constrain velocity locally using gradient constraints from nearby pixels

$$0 = ul'_{x1} + vl'_{y1} + l'_t$$
$$0 = ul'_{x} + vl'_{y} + l'_t$$
$$\dots$$
$$0 = ul'_{x2} + vl'_{y2} + l'_t$$

x1,y1	x,y1	x2,y1
x1,y	**x,y**	x2,y
x1,y2	x,y2	x2,y2

-> *overdetermined* system of equations,

can be solved by *Least-Squares Estimation* (LSE)

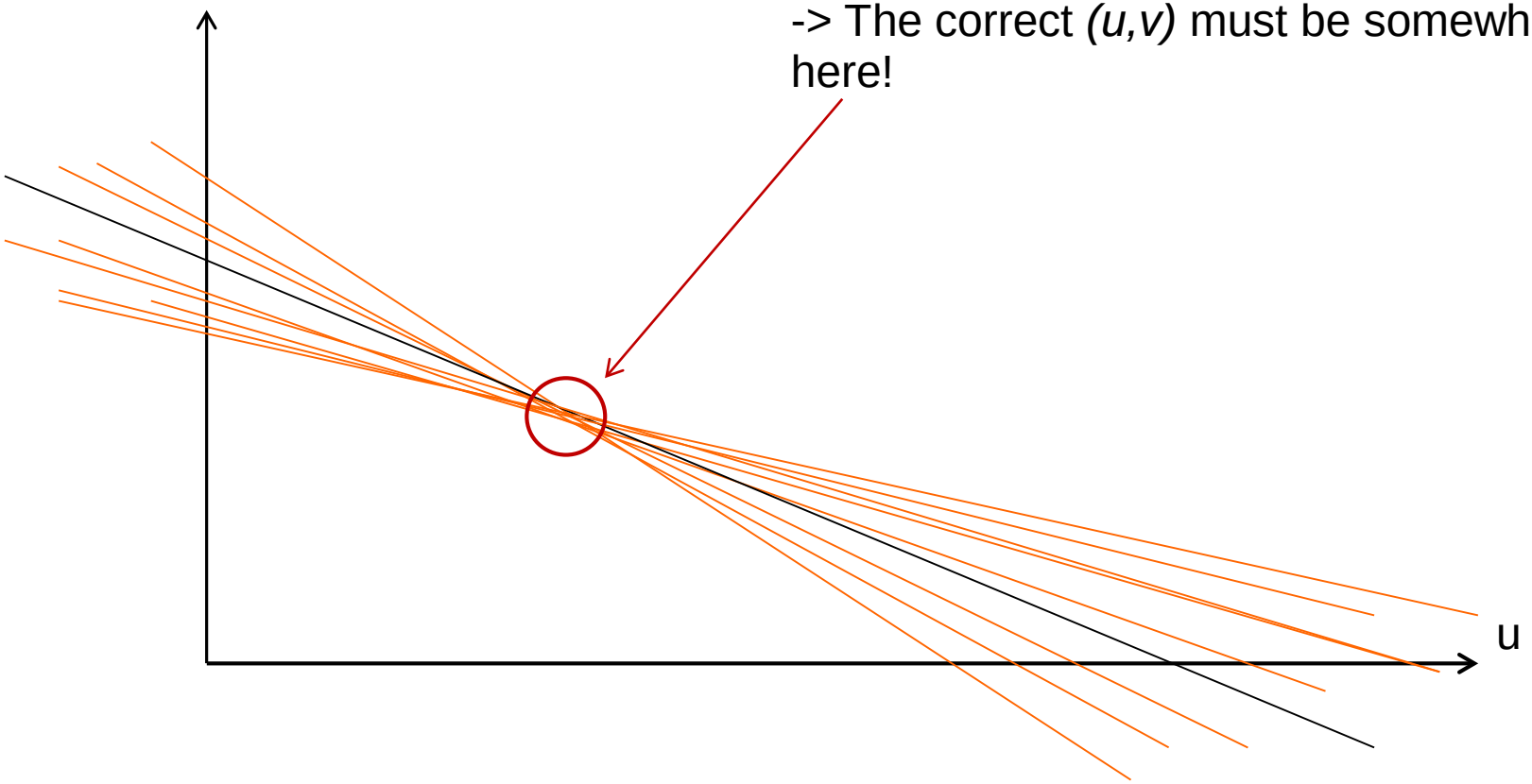
- **Energy function** which is minimized by using LSE:

$$E(u,v) = \sum (ul'_x + vl'_y + l'_t)^2$$

Lucas-Kanade

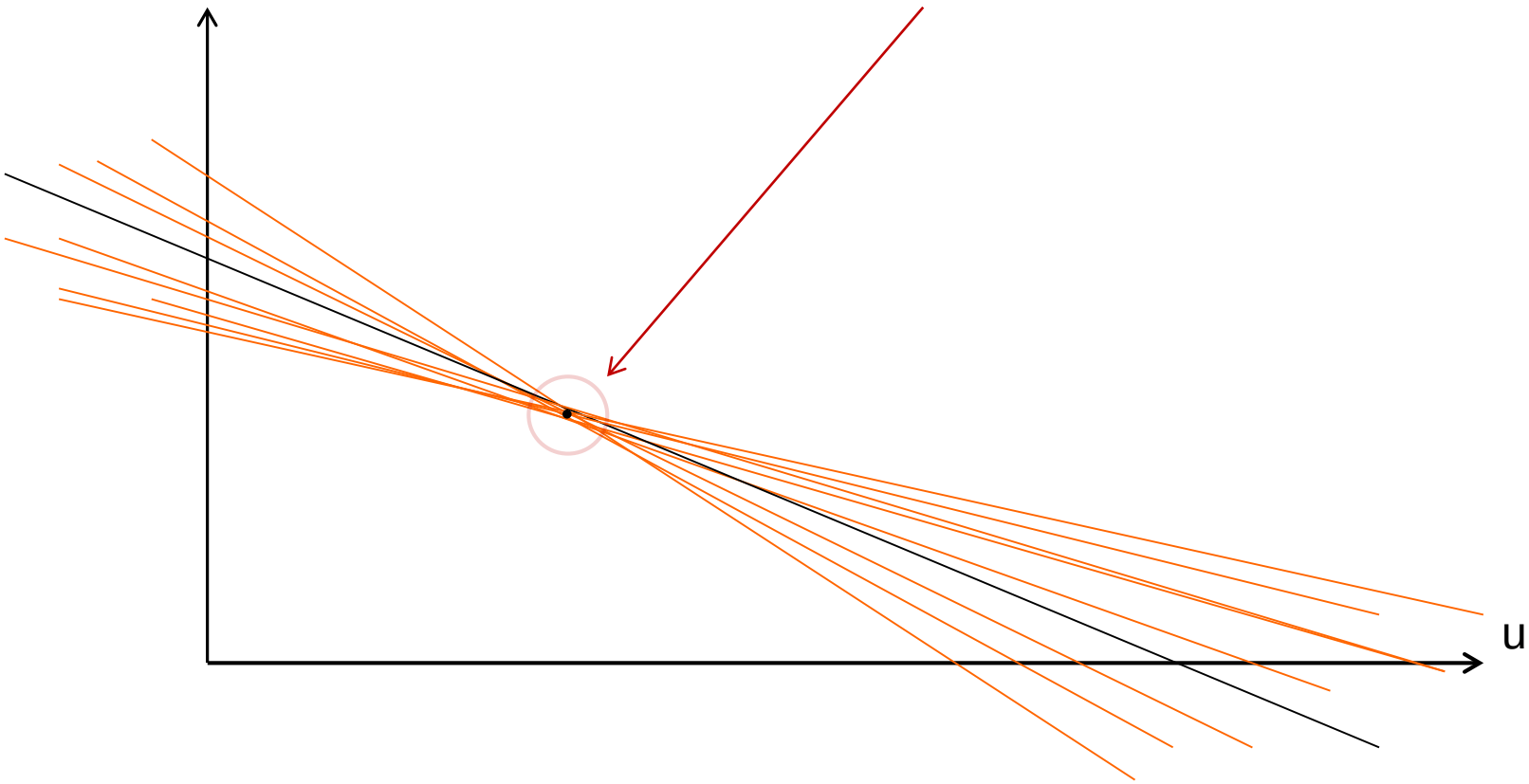
Constraint lines from nearby pixels cluster around a point in this area.

-> The correct *(u,v)* must be somewhere here!



Lucas-Kanade

LSE finds the ‚optimal‘ interception point, concerning the distances from all constraint lines.

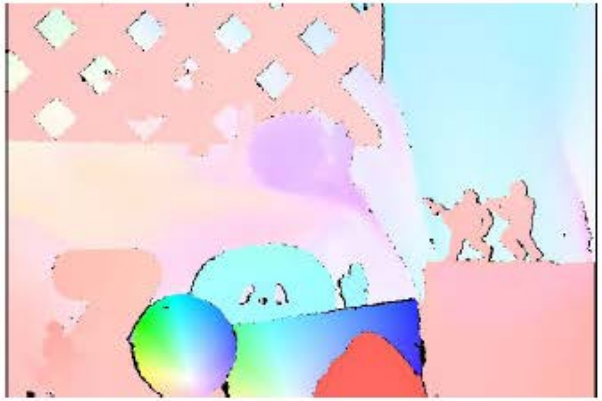


Lucas-Kanade

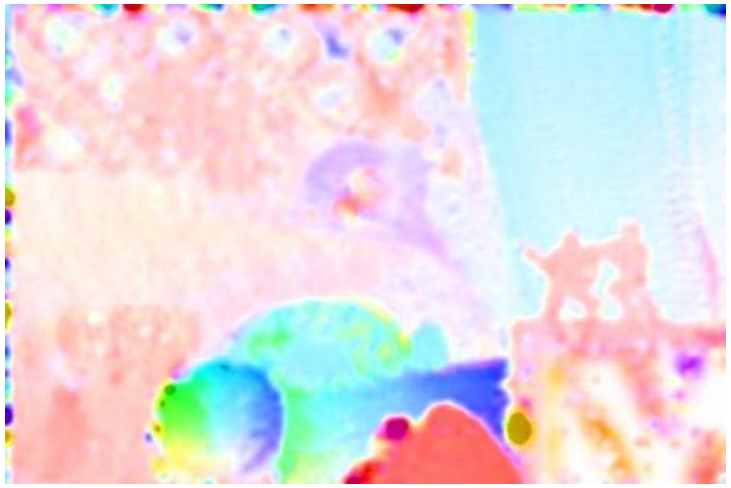
Frame 0

Frame 1

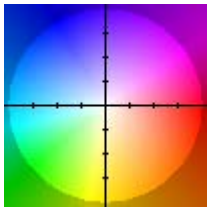
Correct Solution



Estimation Result



Error



OF-vectors are color coded

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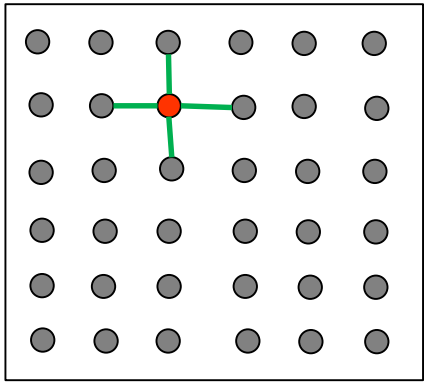
Lucas-Kanade

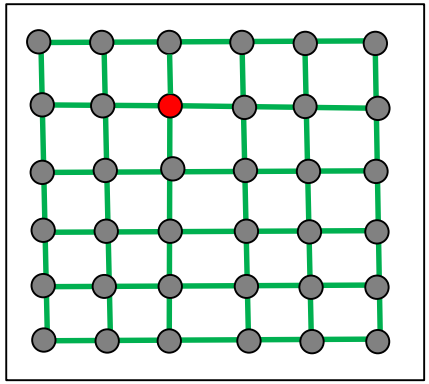
- **Advantages**
  - Dense vector field, no block artifacts
  - More efficient and reliable than block matching
  - Noise is smoothed, but still noisy result!
  - Good results in textured regions
  - Easy and fast calculation
- **Disadvantages**
  - Useless in textureless regions
  - Underestimation of large displacement
  - Errors at boundaries
  - Problems caused by the brightness constancy assumption

Horn-Schunck

- **Basic Idea:** Assume overall smoothness of the resulting flow field.

Local Constraint **vs.** **Global Constraint**





constrains the vector for a pixel by constrains of neighbors

e.g. Lucas-Kanade

constrains the vector for a pixel by average vector of all other pixels

e.g. Horn-Schunck

Horn-Schunck

quadric **penalty functions**

partial derivatives

regularization parameter for degree of smoothness

$$E(u,v) = \iint \left[(u I'_x + v I'_y + I'_t)^2 + \alpha \left(|\nabla u|^2 + |\nabla v|^2 \right) \right] dx\,dy$$

Data Term:

- Applies brightness constancy assumption
- Optical flow equation

- Large for large deviations from brightness constancy assumption
- Small if brightness constancy assumption holds

Smoothness Term:

- Applies smoothness assumption
- First derivatives

- Large if flow field is not smooth
- Small if flow field is smooth

By minimizing this function, solutions which are true for both constrains are favored above others. Wrong solutions are *penalized* with large values.

Horn-Schunck / Energy Function

$$E(u,v) = \iint \left[(uI'_x + vI'_y + I'_t)^2 + \alpha(|\nabla u|^2 + |\nabla v|^2) \right] dx\,dy$$

- **Filling-in-Effect**:

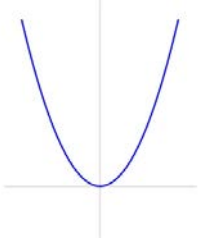
  If there is no information available (e.g. regions of nearly uniform intensity)

$$(uI'_x + vI'_y + I'_t)^2 \approx I'^2_t$$

the smoothness term takes over and „fills in“ the optical flow vectors from nearby pixels (adapt to local solution).

Horn-Schunck / Minimization

$$E(u,v) = \iint \left[(ul'_x + vl'_y + l'_t)^2 + \alpha(|\nabla u|^2 + |\nabla v|^2) \right] dx\,dy$$



E(.) is a **convex function.**

Euler-Lagrange Equations: The first variation of the energy functional (≈first derivate) must vanish.

L1: $(ul'_x + vl'_y + l'_t)l'_x - \alpha(\Delta u) = 0$

L2: $(ul'_x + vl'_y + l'_t)l'_y - \alpha(\Delta v) = 0$

L1: $(l'^2_x + \alpha)u + vl'_y l'_x = \alpha\bar{u} - l'_t l'_x$

L2: $ul'_y l'_x + (l'^2_y + \alpha)v = \alpha\bar{v} - l'_t l'_y$

Δ … Laplace Gradient can be approximated by nearby pixels:

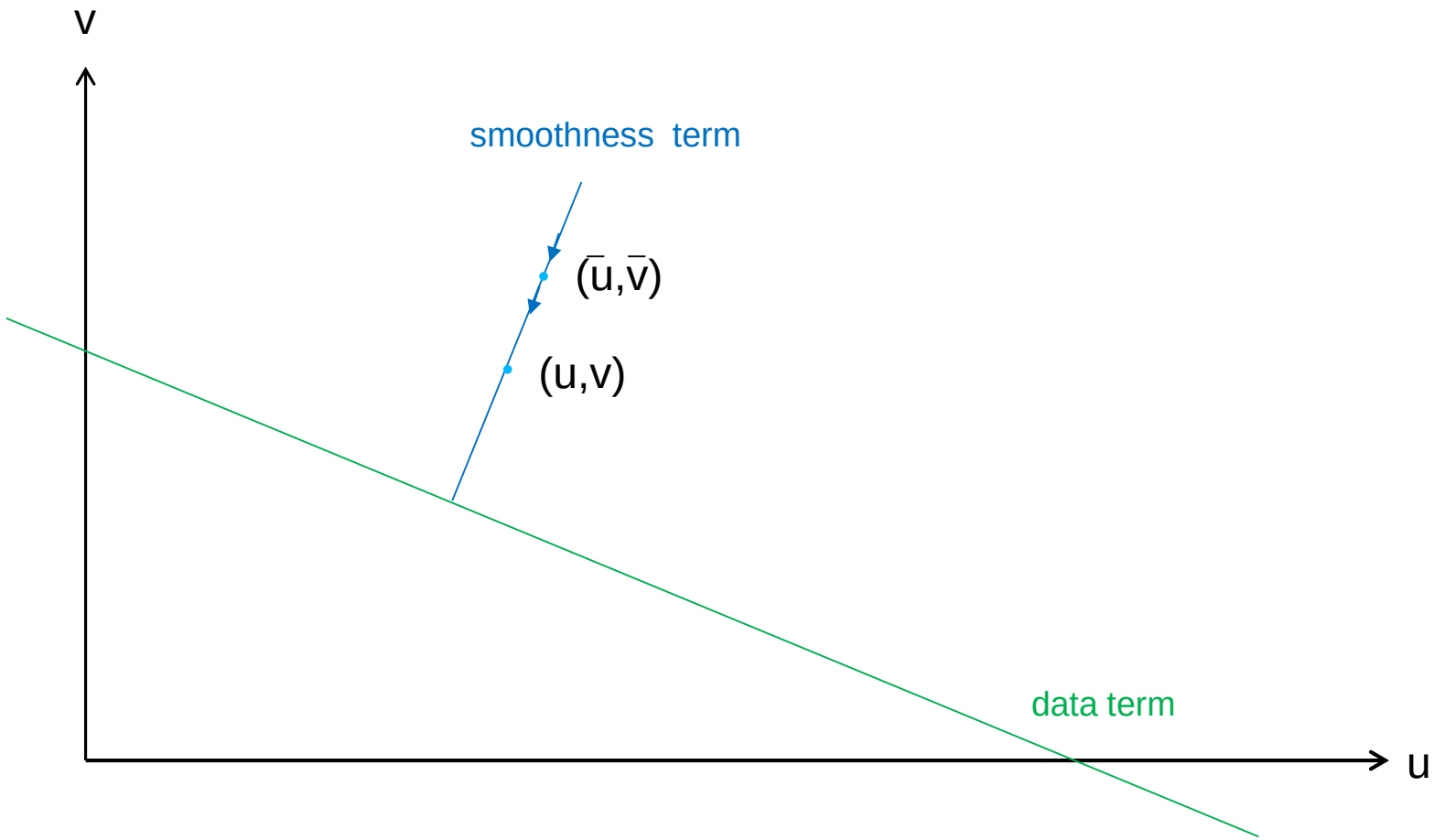
$$\Delta u = \bar{u} - u$$

Solved *iteratively*. Gets more precise with every iteration.

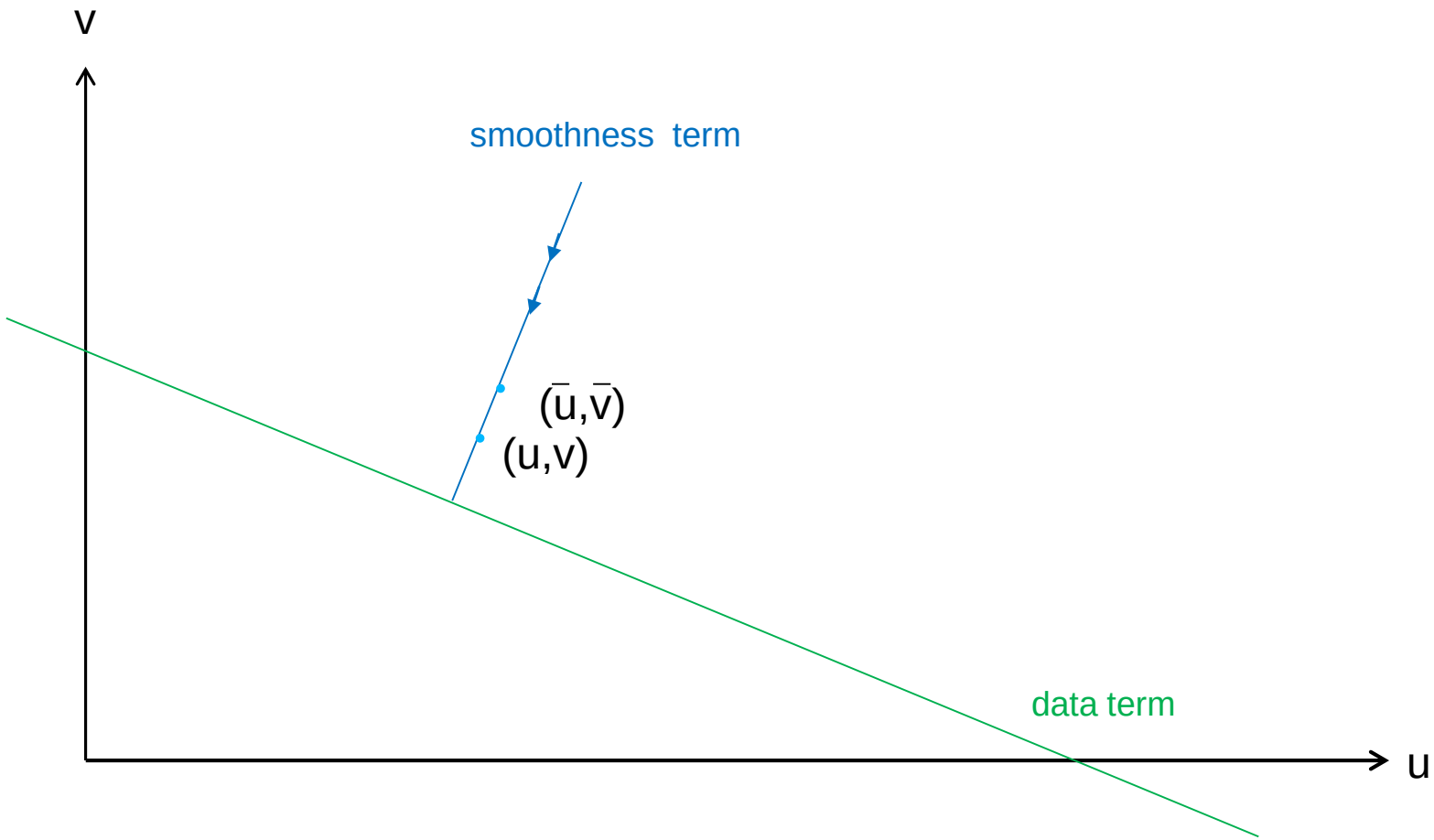
$$u = \bar{u} - \frac{(\bar{u}l'_x + \bar{v}l'_y + l'_t)l'_x}{l'^2_x + l'^2_y + \alpha}$$

$$v = \bar{v} - \frac{(\bar{u}l'_x + \bar{v}l'_y + l'_t)l'_y}{l'^2_x + l'^2_y + \alpha}$$

Horn-Schunck



Horn-Schunck

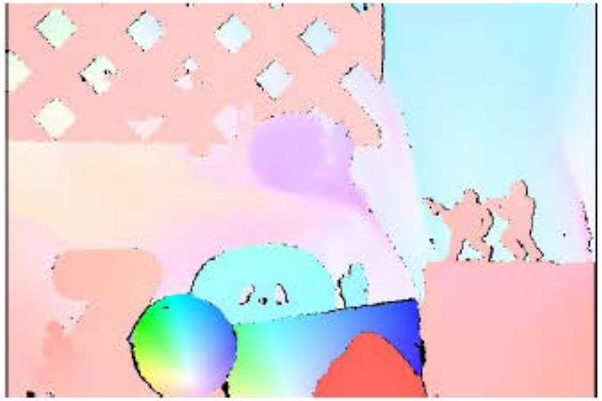


Horn-Schunck

Frame 0

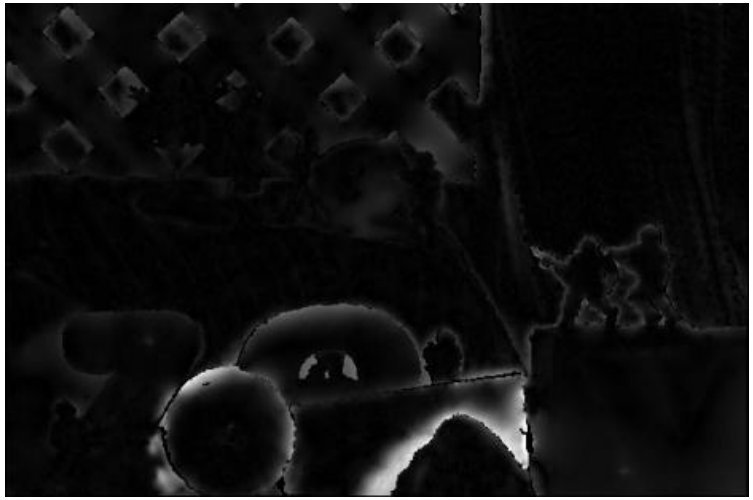
Frame 1

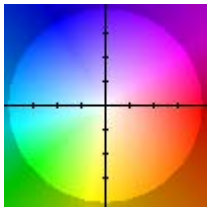
Correct Solution



Estimation Result

Error





OF-vectors are color coded

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Horn-Schunck

- **Advantages**
  - Incorporates global information (“filling-in”)
  - Smooth flow
  - Good results for untextured regions

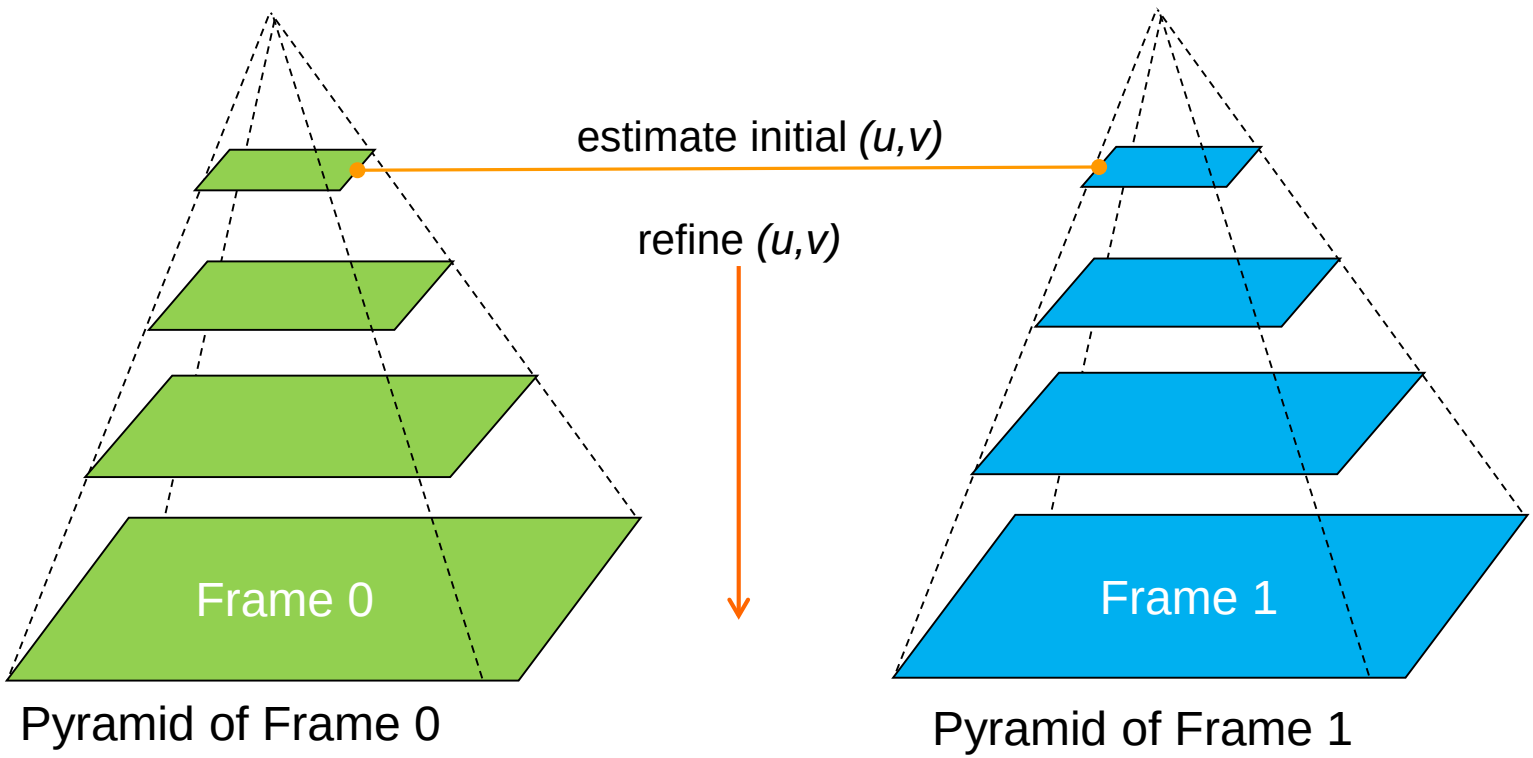
- **Disadvantages**
  - Oversmoothing of motion boundaries
  - Underestimation of large displacements
  - Iterative: slow

  - Problems caused by the brightness constancy assumption

Challenges

Large displacements

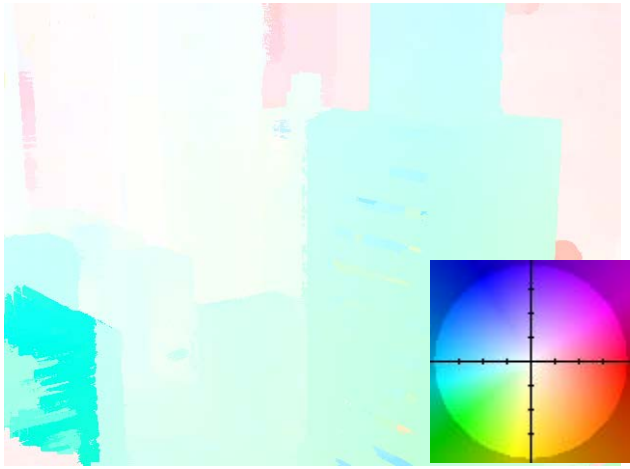
- **Problem:** Approximation of image derivatives does not work for large movement. HS and LK work only for small movements.
- **Solution**: *Coarse-to-fine estimation* using image pyramids



Large displacements

- **Problem:** Approximation of image derivatives does not work for large movement. HS and LK work only for small movements.
- **Solution**: Use a different optimization method, e.g.**,** ***Cost-Volume Filtering****.*
  - **Labels**: Vectors that represent the motion (i.e., *x,y* displacement).
  - **Costs-Volume**: Cost being moved according to a specific vector.
  - **Result**: Motion vectors.

Input: Frame 1 Frame 2 *Output*: Motion [7]



Large displacements

- **Problem:** Approximation of image derivatives does not work for large movement. HS and LK work only for small movements.
- **Solution**: Use a different optimization method, e.g.**,** ***Cost-Volume Filtering****.*
  - **Labels**: Vectors that represent the motion (i.e., *x,y* displacement).

New problem: Scalability of the optical flow estimation algorithm.

- Cost computation for a huge amount of labels (motion vectors).
- Filtering of many cost-volumes!

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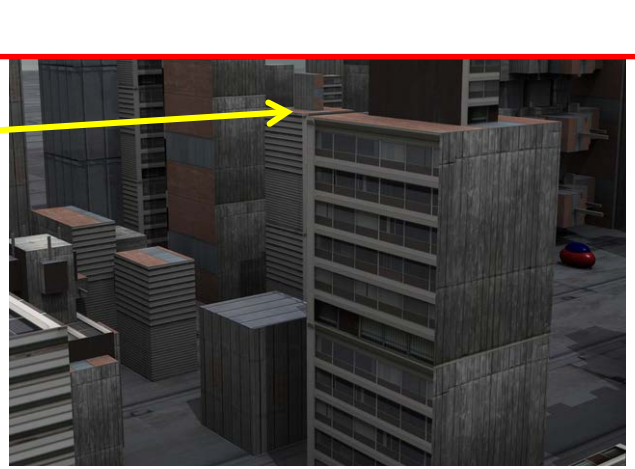
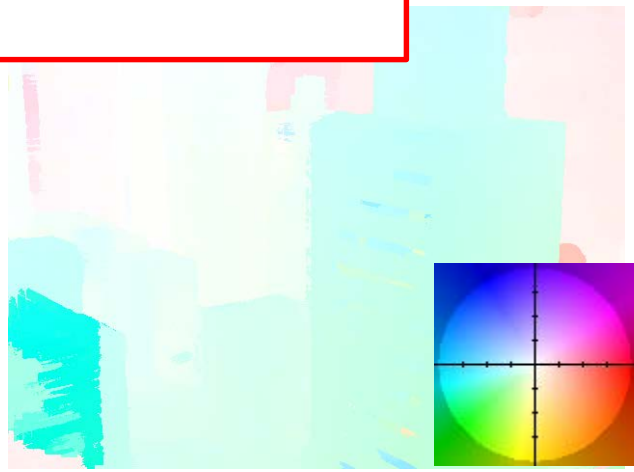




Illumination Changes

- **Problem:** Illumination Changes, e.g., caused by:
  - Shadows
  - Different viewing angles
  - Light source flickering
  - Self-adaptive cameras

- **Solution 1:** Gradient Constancy Assumption
- **Solution 2:** Descriptive Features
- **Solution 3**: HSV Color Model

Illumination Changes: Gradient Constancy Assumption

- **Solution 1** : ***Gradient* constancy assumption**

Assumes that intensity changes are constant.

spatial gradient:

$$\nabla = \partial_x, \partial_y$$

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

Frame 0

Frame 1

The *gradient* constancy assumption is used the same way as the *brightness* constancy assumption.

Illumination Changes: Gradient Constancy Assumption

- **Advantages:**
  - Two more equations
  - Invariant to additive brightness changes

- **Disadvantages:**
  - Not rotation invariant
  - Very noise sensitive

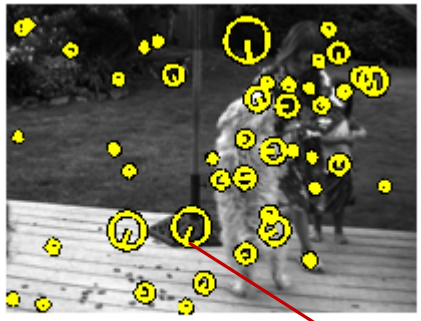
Brightness Constancy and Gradient Constancy both have desired and not wanted effects, which complement each other -> Combine them!

$$E = E_{brightness} + E_{gradient}$$

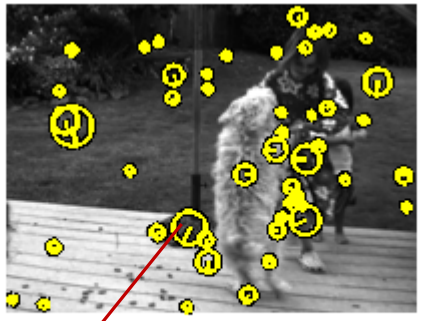
- **Solution 2** : **Descriptive Features**
  - e.g. **SIFT-Features**: Scale Invariant Features

    Points, that can be extracted to provide a description of an object.

    This description can be used to locate the object in another image.



Frame 0



Frame 1

e.g., SIFT-Matching: These are corresponding SIFT keypoints.

-> compute (u,v) from their locations in Frame 0 and Frame 1.

Illumination Changes: Descriptive Features

- **Advantages:**
  - Less sensitive to image deformations
  - Large motion is possible
  - Parts of the object can be occluded

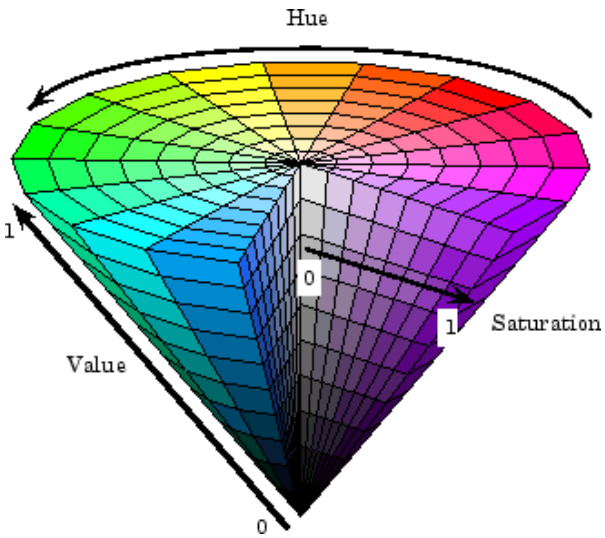
- **Disadvantages:**
  - We don‘t get a dense flow field!

    One Flow vector per SIFT point. If we interpolate these vectors over the whole image -> low accuracy, especially at motion boundaries.
  - Combination with common methods: Descriptive features would need special treatment in optimization process.

Illumination Changes: HSV Color Model

- **Solution 3**: **Spherical Color Model** e.g. HSV
  - **Hue** (H): Color
  - **Saturation** (S)

  Invariant to multiplicative illumination changes (e.g. shadows, shading)
  - **Value** (V): Brightness



$$E = E(H) + E(S) + E(V)$$

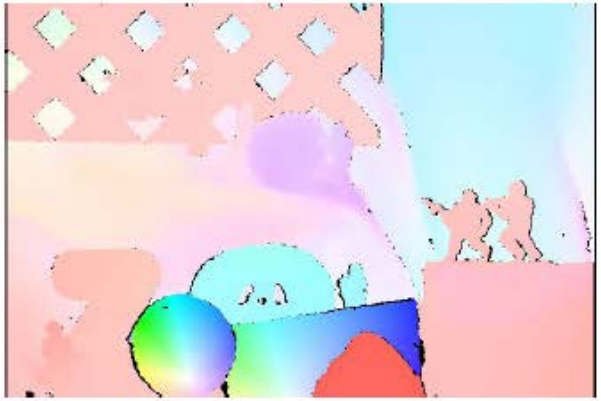
-> picks invariant components when needed

Evaluation

- **Ground Truth (GT)**

Frame 0

Frame 1



GT

Ground Truth: The correct solution (e.g., flow field) for a given problem

- The absence of GT data has represented a major problem in computer vision
- Computer-generated GT images do often not reflect the challenges of real data recorded with a camera.
- It is difficult to measure the progress in a field if there is no commonly agreed data set with GT solution.

[1]

Middlebury Data Set

- **Ground truth (GT) for 12 image sequences**
  - 3 computer generated sequences
  - 9 recorded sequences
- **Quality Evaluation in the Middlebury Benchmark**
  - **Error metrics:**
    - **Angular error** (AE): angle between GT-vector and result
    - **Endpoint error** (EE): Euclidean distance between vectors – more reliable!
    - **Interpolation error** (IE): difference GT and intermediate image
    - **Normalized interpolation error** (NE) : normalized IE
  - **Region Masks**
    - All not occluded pixels
    - Untextured regions
    - Pixels near motion discontinuities
  - **Statistics (accuracy, robustness, …)**

Middlebury Data Set / Online Evaluation

http://vision.middlebury.edu/flow/

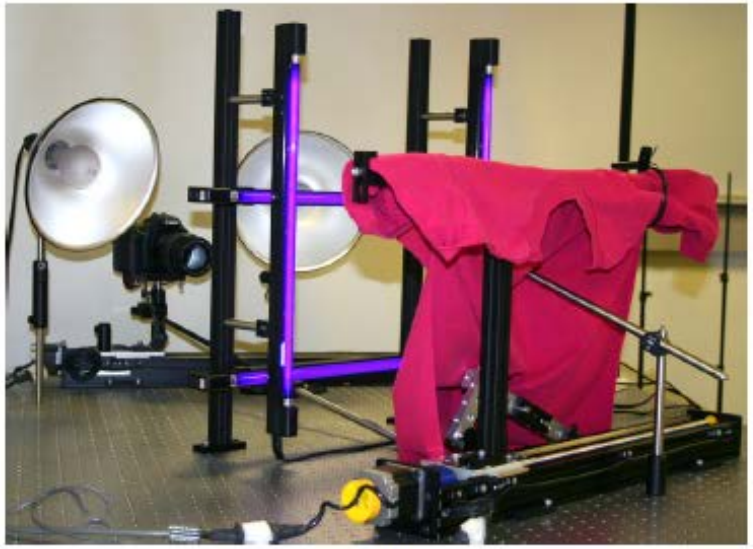
Optical flow evaluation results

Statistics: Average SD R0.5 R1.0 R2.0 A50 A75 A95
Error type: endpoint angle interpolation normalized interpolation

| Average endpoint error | avg. rank | Army (Hidden texture) GT all | Army im0 all | Army im1 all | Army GT disc | Army im0 disc | Army im1 disc | Army GT untext | Army im0 untext | Army im1 untext | Mequon (Hidden texture) GT all | Mequon im0 all | Mequon im1 all | Mequon GT disc | Mequon im0 disc | Mequon im1 disc | Mequon GT untext | Mequon im0 untext | Mequon im1 untext | Schefflera (Hidden texture) GT all | Schefflera im0 all | Schefflera im1 all | Schefflera GT disc | Schefflera im0 disc | Schefflera im1 disc | Schefflera GT untext | Schefflera im0 untext | Schefflera im1 untext | Wooden (Hidden texture) GT all | Wooden im0 all | Wooden im1 all | Wooden GT disc | Wooden im0 disc | Wooden im1 disc | Wooden GT untext | Wooden im0 untext | Wooden im1 untext | Grove (Synthetic) GT all | Grove im0 all | Grove im1 all | Grove GT disc | Grove im0 disc | Grove im1 disc | Grove GT untext | Grove im0 untext | Grove im1 untext | Urban (Synthetic) GT all | Urban im0 all | Urban im1 all | Urban GT disc | Urban im0 disc | Urban im1 disc | Urban GT untext | Urban im0 untext | Urban im1 untext | Yosemite (Synthetic) GT all | Yosemite im0 all | Yosemite im1 all | Yosemite GT disc | Yosemite im0 disc | Yosemite im1 disc | Yosemite GT untext | Yosemite im0 untext | Yosemite im1 untext | Teddy (Stereo) GT all | Teddy im0 all | Teddy im1 all | Teddy GT disc | Teddy im0 disc | Teddy im1 disc | Teddy GT untext | Teddy im0 untext | Teddy im1 untext |
|---|---|---

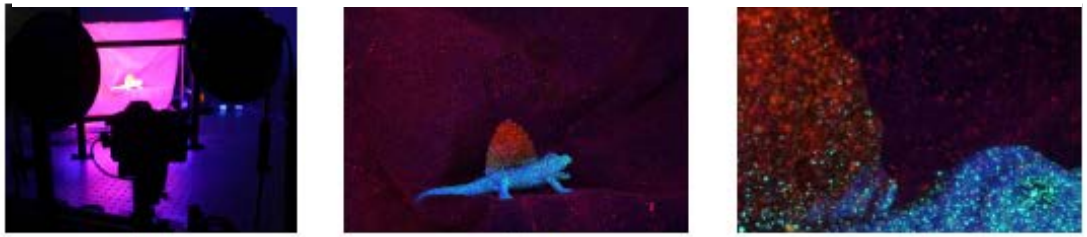
Middlebury Data Set / GT

- **How do they generate GT data?**
  - **Hidden fluorescent texture / splatter pattern in scene**
    - High resolution images in UV + ambient light, motion < 2 pixels
    - *Test sequences*: Every 40th ambient light-frame, downsample images
    - *GT*: Tracking of small windows in original UV sequence



Setup for obtaining GT flow

Setup under visible illumination



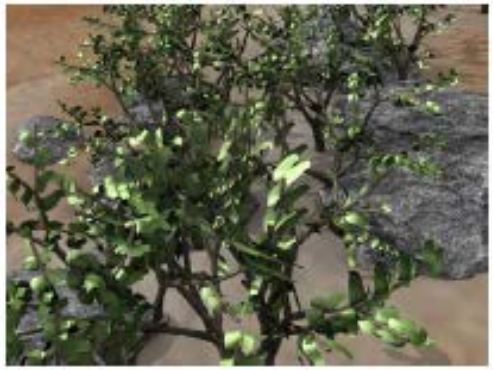
Setup under UV illumination [1]

Middlebury Data Set / GT

- **How do they generate GT data?**
  - **Realistic Synthetic Imagery**
    - Generated with Renderman
    - *Test sequence*: Downsampled images
    - *GT*: Project to 3D motion of the scene to 2D

Frame 0

Frame 1



GT, flow field

[1]

Middlebury Data Set / GT

- **How do they generate GT data?**
  - **Frame interpolation imagery**
    - Record scene with a high-speed camera: 60 frames / second
    - *Test sequences*: skip some frames from recorded sequence
    - *GT*: consists of image frames, use skipped frames as GT
    - Own frame interpolation algorithm to compare performance at same conditions

Frame 0

Frame 1

GT, interpolated frame

[1]

MPI-Sintel Flow Dataset

The **Sintel Flow Dataset** provides naturalistic synthetic videos that are *challenging for current methods*. It is designed to encourage research on *long-range motion*, *motion blur*, *multi-frame analysis*, *non-rigid motion*.

http://sintel.is.tue.mpg.de/

Summary

- **Optical Flow** is the movement of intensity patterns in the image.
- **Techniques:** There are various approaches to estimate optical flow, which differ in how they handle the three key problems of motion estimation.

  e.g. Block Matching

  e.g. Feature Matching

  e.g. Gradient-based Methods

  e.g. Local Methods

  e.g. Global Methods
- **Challenges:** Optical Flow estimation poses many challenges, which several approaches try to overcome.

  e.g. Illumination changes

  e.g. Noise and occlusions

  e.g. Oversmoothing

  e.g. Large/fast motion

  e.g. Untextured regions
- **Evaluation:** The Middlebury Dataset offers test sequences and their GT, which can be used to evaluate Optical Flow Estimation algorithms.

Sample Exam Questions

- How are the key problems solved for e.g., the HS method?
- What is the brightness constancy? What is the Optical Flow Equation?
- Explain the relationship of 2D motion and OF. Give examples.
- Compare the HS and LK method.
- Explain a challenge and a possible solution for it.
- Where and how can you evaluate an OF algorithm?
- What is the aperture problem?
- List three applications of optical flow.

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