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## MOTION & TRACKING

**Readings:**

Szeliski: Chapter 8.1,8.2,8.4

Some Slides adapted from Univ. of Washington

Additional material by courtesy of Tomas Svoboda  
svoboda@cmp.felk.cvut.cz

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### Why estimate visual motion?

- Visual Motion can be annoying
  - Camera instabilities, jitter
  - Measure it; remove it (stabilize)
- Visual Motion indicates dynamics in the scene
  - Moving objects, behavior
  - Track objects and analyze trajectories
- Visual Motion reveals spatial layout
  - Motion parallax

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### TX-Clip

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## Motion

- Motion Blur
- Motion Detection
  - Find movement
- Moving Object Detection and Location
  - Motion Based Segmentation
  - Trajectories → Tracking
- Shape from Motion
  - Similar to Stereo
  - Optical Flow

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## Motion

Information about *scene motion* rather than the *scene*.

an "image cube"  
 $I(x,y,t)$

time

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## Process of images over time.

Image sequence:

- An **image sequence** is a series of  $N$  images, or frames, acquired at discrete time instants  $t_k = t_0 + k\Delta t$ , where  $\Delta t$  is a fixed time interval and  $k = 0, 1, \dots, N-1$

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Motion Blur

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Image distortion

$$g(i, j) = s \left[ \iint_{(a,b) \in O} f(a, b) h(a, b, i, j) da db \right] + v(i, j)$$

↓ assuming linearity

$$g(i, j) = (f * h)(i, j) + v(i, j)$$

↓ f-domain (Fourier transform)

$$G(u, v) = F(u, v)H(u, v) + N(u, v)$$

g(i,j) ... degraded image  
 f(a,b) ... original image  
 h(...) ... distortion function  
 v(i,j) ... noise

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Inverse filtration

$$F(u, v) = G(u, v)H^{-1}(u, v) - N(u, v)H^{-1}(u, v)$$

Relative motion of camera and object

$$H(u, v) = \frac{\sin(\pi VTu)}{\pi Vu}$$

V ... constant speed in x-axes  
 T ... shutter open time

Poor results in presence of noise → Wiener filter

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Inverse filtration example

Blurred Image



Simple inverse filtration



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Wiener filtration


Blurred + noise added



Simple inverse filtration



Wiener filtration



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Motion Detection

- Separating background and foreground
  - static scene (background)
  - moving objects (foreground)
  
- Detect meaningful motions
  
- Problems:
  - shadows
  - objects that temporarily stopped
  - moving camera / background

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Motion Detection with Static Camera

- Frame Differencing:
 
$$d(x, y) = \begin{cases} 0 & |f_t(x, y) - f_{t+1}(x, y)| < \varepsilon \\ 1 & \text{sonst} \end{cases}$$

The figure shows three side-by-side images. The first image is labeled  $f(x,y)$  and shows a room with desks and computers. The second image is labeled  $f_{t+1}(x,y)$  and shows the same room with a person's legs visible in the foreground. The third image is labeled  $d(x,y)$  and is a heatmap where the area where the person's legs were is colored red, indicating motion, while the rest of the room is blue.

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Motion Detection with Static Camera

- Frame Differencing (Thresholds)

The figure shows four grayscale images of a person walking in a hallway, arranged in a 2x2 grid. The top-left image is the original frame. The top-right image is the frame with a threshold applied, showing the person as white against a black background. The bottom-left image is the frame with a different threshold applied, showing a different result. The bottom-right image is the frame with a third threshold applied, showing another result.

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Motion Detection with Static Camera

- Background Substraction
 
$$d(x, y) = \begin{cases} 0 & |f_t(x, y) - B(x, y)| < \varepsilon \\ 1 & \text{sonst} \end{cases}$$

The figure shows three side-by-side images. The first image is labeled  $B(x,y)$  and shows a room with desks and computers. The second image is labeled  $f(x,y)$  and shows the same room with a person's legs visible in the foreground. The third image is labeled  $d(x,y)$  and is a heatmap where the area where the person's legs were is colored red, indicating motion, while the rest of the room is blue.

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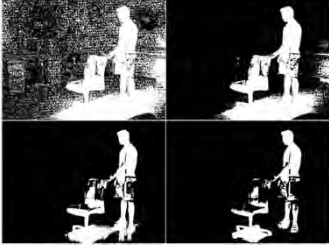
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## Motion Detection with Static Camera

- Frame Differencing (Thresholds)



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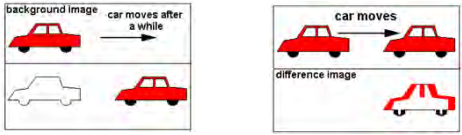
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## Motion Detection Summary

Problems:

- **Background subtraction:**
  - How to get background model?
  - When to update
  - Holes
- **Frame differencing:**
  - Parts of object
  - Timescale of frames
  - Threshold



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## Motion Detection

Surveillance:



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## Motion Analysis Problems

**Correspondence Problem**

- Track corresponding elements across frames

**Reconstruction Problem**

- Given a number of corresponding elements, and camera parameters, what can we say about the 3D motion and structure of the observed scene?

**Segmentation Problem**

- What are the regions of the image plane which correspond to *different* moving objects?

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## Motion field

Vector field where each vector represents motion of point across image at time interval  $dt$

**Optical Flow**

Image sequence:

- Spatial- and Temporal sampling
- Temporal sampling needs to be high
- Correspondence problem (occlusions, etc)

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Assuming that illumination does not change:

Image changes are due to the **RELATIVE MOTION** between the scene and the camera.

There are 3 possibilities:

- Camera still, moving scene
- Moving camera, still scene
- Moving camera, moving scene

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## Optical Flow Examples

Static Camera / Moving Scene



Color-coded

Moving Camera / Moving Scene



WARNING: NOTHING TO OUTPUT  
BFRAME DECODER LAG

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## Motion Field (MF)

The **MF** assigns a velocity vector to each pixel in the image.

These velocities are INDUCED by the RELATIVE MOTION btw the camera and the 3D scene

The **MF** can be thought as the projection of the 3D velocities on the image plane.

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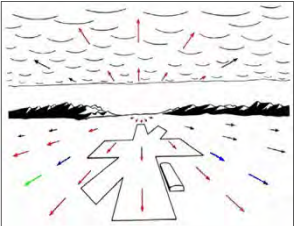
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## Motion Field

Non rotating Camera:

- Vectors are radial to Focus
- **FOE**: Focus Of **Expansion**
- **FOC**: Focus Of **Contraction**
- Point where Motion vectors intersect with the image plane.



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**Motion Field**

Length of vector:

- inversely proportional to distance of point
- proportional to sine of point and movement direction of camera

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**Motion Field**

**Attention:** Motion Vector  $\neq$  Motion

*a*

Moving Ball

*b*

Moving Light source

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**Optical Flow estimation**

Correspondence problem

- sparse vector field
- same problem as stereo

To reliably establish correspondences

- High temporal sampling  $\rightarrow$  small changes
- Constant intensities/edges

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## Optical Flow estimation

**Two assumptions**

1. Observed brightness is constant
2. Nearby points move in similar manner (velocity smoothness)

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## Brightness Constraint

Brightness Constancy Equation:

$$J(x, y) \approx I(x + u(x, y), y + v(x, y))$$

Or, minimize :

$$E(u, v) = (J(x, y) - I(x + u, y + v))^2$$

Linearizing (assuming small  $(u, v)$ ):

$$J(x, y) \approx I(x, y) + I_x(x, y) \cdot u(x, y) + I_y(x, y) \cdot v(x, y)$$

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## Gradient Constraint (or the Optical Flow Constraint)

$$E(u, v) = (I_x \cdot u + I_y \cdot v + I_t)^2$$

Minimizing:  $\frac{\partial E}{\partial u} = \frac{\partial E}{\partial v} = 0$

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

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

In general  $I_x, I_y \neq 0$

Hence,  $I_x \cdot u + I_y \cdot v + I_t \approx 0$

The gradient constraint – only one constraint for each pixel

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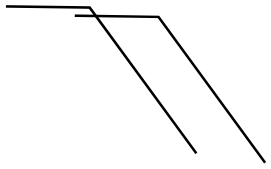
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### Aperture Problem



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The diagram shows two parallel lines that are interrupted by a gap. The top line is horizontal on the left and then slopes downwards on the right. The bottom line is also horizontal on the left and slopes downwards on the right, but it is shifted to the right relative to the top line. This creates a gap between the two lines in the middle.

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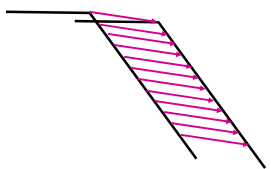
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### Aperture Problem



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The diagram is identical to the one on slide 31, but the parallelogram formed by the two lines and their extensions is shaded in pink.

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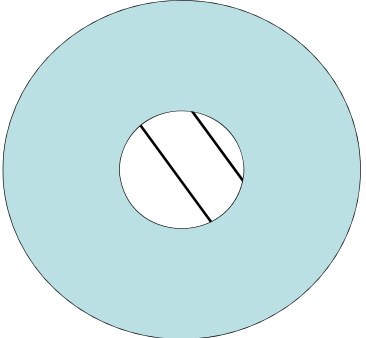
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### Aperture Problem



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The diagram shows a light blue circular aperture with a smaller white circle inside it. Two parallel lines are visible through the white circle, but they are cut off by the inner boundary of the white circle. The lines are parallel to each other and to the horizontal diameter of the white circle.

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**Motion Based Segmentation**

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**Motion Based Segmentation**

- ◆ **Top-Down:**
  - ◆ Global Motion
  - ◆ All regions that are significantly different
- ◆ **Joint estimation / segmentation**
  - ◆ Pixel as Mixture of Motions
  - ◆ Estimate Motion and Segmentation simultaneously
- ◆ **Grouping of elementary regions**
  - ◆ Region Growing Split & Merge, etc.
  - ◆ Use also Gray value information

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**Vision = Inverse Graphics**

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**Tracking = Inverse Animation**

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**Tracking: First Idea!**

initial position    prediction    measurement    update

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**Region tracking** or "BLOB" tracking

old / predicted object location → region of interest → model pixels found → decide on a new object location

predictive model -- update step

recognizing a ping-pong ball by pixel intensity

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## Contour Tracking



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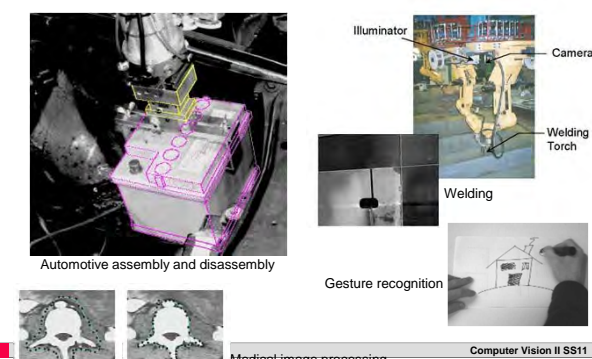
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## Contour-tracking, applied



Automotive assembly and disassembly

Welding

Gesture recognition

Medical image processing

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## Optical Tracking - Animation

multi-camera tracking system:

- real-time motion capturing of actors
- real-time visual feedback
- added redundancy by integrating single view tracking as fallback



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## Tracking for MOCAP



Tracking landmarks to control avatars facial expressions (VIDEO)

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## Tracking f. Augmented Reality



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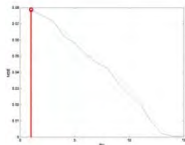
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## Lucas-Kanade Tracking

Find correspondences using a template  
 Estimate „optimal“ Translation  
 Minimize SSD  
 Gradient based Optimization

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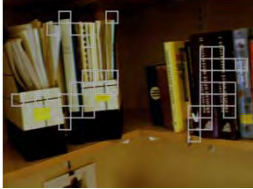
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- Computer Vision Applications:
  - Optical Flow
  - Feature Tracker
    - KLT (Kanade-Lucas-Tomasi Tracking)
  - Widely used



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Lucas & Kanade  
 Derivation

#1

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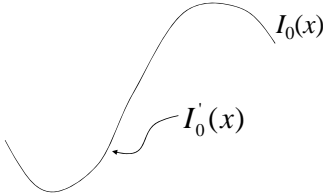
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L&K Derivation 1



$$I'_0(x) = \lim_{h \rightarrow 0} \frac{I_0(x+h) - I_0(x)}{h}$$

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L&K Derivation 1

$$I'_0(x) \approx \frac{I_0(x+h) - I_0(x)}{h}$$

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L&K Derivation 1

$$I'_0(x) \approx \frac{I(x) - I_0(x)}{h}$$

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L&K Derivation 1

$$h \approx \frac{I(x) - I_0(x)}{I'_0(x)}$$

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L&K Derivation 1

$$h \approx \frac{1}{|R|} \sum_{x \in R} \frac{I(x) - I_0(x)}{I_0'(x)}$$

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L&K Derivation 1

$$h \approx \frac{1}{\sum_x w(x)} \sum_{x \in R} \frac{w(x)[I(x) - I_0(x)]}{I_0'(x)}$$

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L&K Derivation 1

$$h_0 \leftarrow \frac{1}{\sum_x w(x)} \sum_{x \in R} \frac{w(x)[I(x) - I_0(x)]}{I_0'(x)}$$

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### L&K Derivation 1

$$h_1 \leftarrow h_0 + \frac{1}{\sum_x w(x)} \sum_{x \in R} \frac{w(x)[I(x) - I_0(x+h_0)]}{I_0'(x+h_0)}$$

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### L&K Derivation 1

$$h_2 \leftarrow h_1 + \frac{1}{\sum_x w(x)} \sum_{x \in R} \frac{w(x)[I(x) - I_0(x+h_1)]}{I_0'(x+h_1)}$$

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### L&K Derivation 1

$$h_{k+1} \leftarrow h_k + \frac{1}{\sum_x w(x)} \sum_{x \in R} \frac{w(x)[I(x) - I_0(x+h_k)]}{I_0'(x+h_k)}$$

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L&K Derivation 1

$$h_{k+1} \leftarrow h_k + \frac{1}{\sum_x w(x)} \sum_{x \in R} \frac{w(x)[I(x) - I_0(x+h_k)]}{I_0'(x+h_k)}$$

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Lucas & Kanade  
Derivation

#2

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L&K Derivation 2

Sum-of-squared-difference (SSD) error

$$E(h) = \sum_{x \in R} [I(x) - I_0(x+h)]^2$$

$$E(h) \approx \sum_{x \in R} [I(x) - I_0(x) - hI_0'(x)]^2$$

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L&K Derivation 2

$$\frac{\partial E}{\partial h} \approx \sum_{x \in R} 2[I_0'(x)(I(x) - I_0(x)) - hI_0'(x)^2]$$

$$= 0$$

$$h \approx \frac{\sum_{x \in R} I_0'(x)(I(x) - I_0(x))}{\sum_{x \in R} I_0'(x)^2}$$

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Comparison

$$h \approx \frac{\sum_x \frac{w(x)[I(x) - I_0(x)]}{I_0'(x)}}{\sum_x w(x)}$$

$$h \approx \frac{\sum_x I_0'(x)[I(x) - I_0(x)]}{\sum_x I_0'(x)^2}$$

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Comparison

$$h \approx \frac{\sum_x \frac{w(x) [I(x) - I_0(x)]}{I_0'(x)}}{\sum_x w(x)}$$

$$h \approx \frac{\sum_x I_0'(x)[I(x) - I_0(x)]}{\sum_x I_0'(x)^2}$$

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Generalizations

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Original

$$E(h) = \sum_{x \in R} [I(x+h) - I_0(x)]^2$$

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Original

Dimension of image

$$E(h) = \sum_{x \in R} [I(x+h) - I_0(x)]^2$$

1-dimensional

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## Generalization 1a

Dimension of image

$$E(\mathbf{h}) = \sum_{\mathbf{x} \in R} [I(\mathbf{x} + \mathbf{h}) - I_0(\mathbf{x})]^2$$

2D:  $\mathbf{x} = \begin{bmatrix} x \\ y \end{bmatrix}$

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## Lucas-Kanade Algorithm

iterate:

- (1) Warp  $I$  with  $\mathbf{W}(\mathbf{x}; \mathbf{p})$  to compute  $I(\mathbf{W}(\mathbf{x}; \mathbf{p}))$
- (2) Compute the error image  $E(\mathbf{x}) = I(\mathbf{W}(\mathbf{x}; \mathbf{p})) - I_0(\mathbf{x})$
- (3) Warp the gradient  $\nabla I$  with  $\mathbf{W}(\mathbf{x}; \mathbf{p})$
- (4) Evaluate the Jacobian  $\frac{\partial E}{\partial \mathbf{p}}$  at  $(\mathbf{x}; \mathbf{p})$
- (5) Compute the steepest descent images  $\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}}$
- (6) Compute the Hessian matrix using Equation (11)
- (7) Compute  $\sum_{\mathbf{x}} (\nabla I \frac{\partial \mathbf{W}}{\partial \mathbf{p}})^T [I(\mathbf{x}) - I_0(\mathbf{x})]$
- (8) Compute  $\Delta \mathbf{p}$  using Equation (10)
- (9) Update the parameters  $\mathbf{p} \leftarrow \mathbf{p} + \Delta \mathbf{p}$

$\|\mathbf{x}\| \leq \epsilon$

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## Problem A

Does the iteration converge?

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### Problem A

Local minima:

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### Problem B

Zero gradient:

$$h \approx \frac{-\sum_{x \in R} I_0'(x)(I(x) - I_0(x))}{\sum_{x \in R} I_0'(x)^2}$$

$h$  is undefined if  $\sum_{x \in R} I_0'(x)^2$  is zero

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### Problem B

Zero gradient:

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Problem B'

Aperture problem:

$$h_y \approx \frac{-\sum_{x \in R} \frac{\partial I_0(\mathbf{x})}{\partial y}(\mathbf{x})(I(\mathbf{x}) - I_0(\mathbf{x}))}{\sum_{x \in R} \left( \frac{\partial I_0(\mathbf{x})}{\partial y} \right)^2}$$

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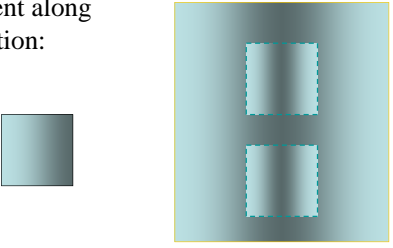
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Problem B'

No gradient along one direction:



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Good Features to Track?

- Textured Regions  
    otherwise Aperture problem
- Harris corners
  - Edge: one eigenvector with eigenvalue zero
  - Homogenous: zero eigenvalues
- Other break-downs:
  - No brightness constancy
  - Nearby points move different (which window size)
  - Too much motion (multi-scale estimation)
  - Occlusions

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## KLT Examples



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## Solutions to A & B

Possible solutions:

- Manual intervention



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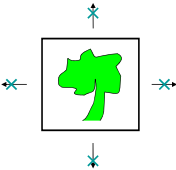
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## Solutions to A & B

Possible solutions:

- Manual intervention
- Zero motion default



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## Solutions to A & B

Possible solutions:

- Manual intervention
- Zero motion default
- Coefficient "dampening"

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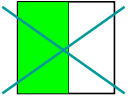
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## Solutions to A & B

Possible solutions:

- Manual intervention
- Zero motion default
- Coefficient "dampening"
- Reliance on good features

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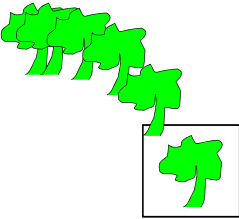
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## Solutions to A & B

Possible solutions:

- Manual intervention
- Zero motion default
- Coefficient "dampening"
- Reliance on good features
- Temporal filtering



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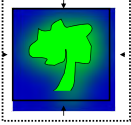
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## Solutions to A & B

Possible solutions:

- Manual intervention
- Zero motion default
- Coefficient "dampening"
- Reliance on good features
- Temporal filtering
- **Spatial interpolation / hierarchical estimation**



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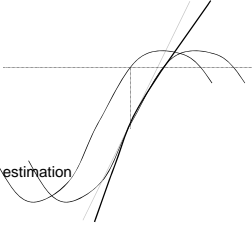
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## Solutions to A & B

Possible solutions:

- Manual intervention
- Zero motion default
- Coefficient "dampening"
- Reliance on good features
- Temporal filtering
- Spatial interpolation / hierarchical estimation
- **Higher-order terms**



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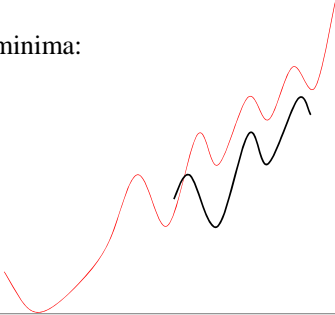
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## Problem A

Local minima:



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## Summary

- Motion Detection Methods
  - Background Subtraction / Frame difference
  - Assumption and Problems
- Motion Field Estimation
  - Assumptions
  - Aperture Problem
- Tracking
  - Main Loop
- Lucas Kanade
  - Principal Idea
  - Problems, Limitations and Solution

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