Computer Vision

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LSEG Challenge

Project 1 – considerations

- got 53 out of ~ 100 submissions
- uploaded the ground-truth annotations in the test set, please check and report errors from our side
- we have run our evaluation code and obtain intermediary results, the final results will be announced in about two weeks time after:
  - carefully checking your code (run some plagiarism software: moss, etc)
  - verifying that your reported results coincide when running your code
  - reading your pdfs (some cool stuff here!)

- not so cool:
  - student uploading zip archives > 500 MB on my Dropbox (we needed only your code ~ 100KB + your results ~1MB)
  - students renaming randomly their files, reading files in the wrong order
  - students uploading their Submissions in Results and the other way round
  - students uploading solution for Task2 as solution for Task1

Project 1 – not so cool

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Project 1 – Intermediary Results

				Task1 - CLASSIC		Task2 - JIGSAW		Task3 - CUBE				
Nr.	**Nume**	**Prenume**	**Grupa**	**Correct**	**Points**	**Correct**	**Points**	**Correct**	**Points**	**Drawings**	**Points**	**Total**
1	Badea-Armeanu	Razvan-Ilie	405	41	2.05	0	0	0	0	0	0	**2.55**
2	Onetiu	Radu	405									
3	Apostu	Robert	406	48	2.4	37	1.85	10	0.5	10	0.5	**5.75**
4	Bolun	Valeria	406	41	2.05	0	0	0	0	0	0	**2.55**
5	Ciltea	Marian	406	49	2.45	0	0	0	0	0	0	**2.95**
6	Costachi	Ana Maria	406	2	0.1	0	0	0	0	0	0	**0.6**
7	Darii	Dan	406	46	2.3	40	2	0	0	0	0	**4.8**
8	Ionescu	Andrei	406	49	2.45	38	1.9	0	0	4	0.2	**5.05**
9	Matei	Bianca-Gabriela	406	47	2.35	40	2	5	0.25	10	0.5	**5.6**
10	Petrasco	Sandu	406	48	2.4	38	1.9	10	0.5	10	0.5	**5.8**
11	Pogonaru	Stefan	406	46	2.3	16	0.8	0	0	0	0	**3.6**
12	Cazacu	Razvan Marian	407	42	2.1	0	0	0	0	0	0	**2.6**
13	Chitu	Irina-Nicoleta	407	47	2.35	19	0.95	0	0	0	0	**3.8**
14	Cojocariu	Sebastian	407	50	2.5	40	2	10	0.5	10	0.5	**6**
15	Curea	Paul-Andrei	407	50	2.5	40	2	10	0.5	10	0.5	**6**
16	Dorcioman	Razvan	407	48	2.4	38	1.9	4	0.2	9	0.45	**5.45**
17	Dumitrascu	Claudiu-Cristian	407	32	1.6	31	1.55	0	0	0	0	**3.65**
18	Dumitru	Victor-Tiberiu	407	1	0.05	0	0	0	0	0	0	**0.55**
19	Enescu	Alexandra-Mihaela	407	35	1.75	0	0	0	0		0	**2.25**
20	Filipescu	Stefan-Gabriel	407	27	1.35	0	0	0	0	0	0	**1.85**
21	Florescu	Andrei	407	47	2.35	35	1.75	0	0	0	0	**4.6**
22	Ghadamiyan	Lida	407	48	2.4	0	0	0	0	9	0.45	**3.35**
23	Gidea	Andrei	407	48	2.4	36	1.8	9	0.45	9	0.45	**5.6**
24	Ginga	Raluca-Andreea	407	33	1.65	27	1.35	0	0	4	0.2	**3.7**
25	Henning	Erik	407	46	2.3	0	0	0	0	0	0	**2.8**
26	Iancu	Andrei	407	48	2.4	28	1.4	0	0	0	0	**4.3**
27	Ionescu	Diana	407	20	1	0	0	0	0	0	0	**1.5**
28	Iordache	Adrian-Razvan	407	49	2.45	39	1.95	10	0.5	10	0.5	**5.9**

Project 1 – Intermediary Results

				Task1 - CLASSIC		Task2 - JIGSAW		Task3 - CUBE				
Nr.	**Nume**	**Prenume**	**Grupa**	**Correct**	**Points**	**Correct**	**Points**	**Correct**	**Points**	**Drawings**	**Points**	**Total**
29	Manghiuc	Teodor-Florin	407	45	2.25	0	0	0	0	0	0	**2.75**
30	Maria	Andrei-Cosmin	407	44	2.2	0	0	10	0.5	10	0.5	**3.7**
31	Mindrescu	Andu	407	40	2	28	1.4	0	0	0	0	**3.9**
32	Moscu	Madalina	407	48	2.4	40	2	10	0.5	10	0.5	**5.9**
33	Nicolicioiu	Armand	407	45	2.25	38	1.9	10	0.5	10	0.5	**5.65**
34	Ouatu	Bogdan	407	49	2.45	40	2	0	0	0	0	**4.95**
35	Partu	Ana-Maria	407	48	2.4	35	1.75	10	0.5	10	0.5	**5.65**
36	Patrascu	Valentin	407	48	2.4	38	1.9	10	0.5	10	0.5	**5.8**
37	Popa	Larisa	407									
38	Popescu	Teodor	407	50	2.5	39	1.95	10	0.5	10	0.5	**5.95**
39	Purcea	Florin-Daniel	407	43	2.15	38	1.9	9	0.45	9	0.45	**5.45**
40	Radu	Alexandra-Raluca	407									
41	Secatureanu	Vlad	407	41	2.05	0	0	0	0	0	0	**2.55**
42	Sielecki	Bogdan Radu Silviu	407	46	2.3	38	1.9	10	0.5	10	0.5	**5.7**
43	Sotir	Anca-Nicoleta	407	49	2.45	19	0.95	0	0	0	0	**3.9**
44	Sumedrea	Paul	407	47	2.35	20	1	0	0	0	0	**3.85**
45	Toader	Liviu-Eduard	407	49	2.45	39	1.95	0	0	0	0	**4.9**
46	Acsintoae	Andra Maria	411	41	2.05	2	0.1	0	0	5	0.25	**2.9**
47	Chirila	Diana-Gabriela	411	49	2.45	20	1	0	0	0	0	**3.95**
48	Chirita	Catalina Elena	411	wrong format								
49	Fulea	Andrei	411	46	2.3	0	0	0	0	0	0	**2.8**
50	Menadil	Rafael-Edy	411	16	0.8	0	0	0	0	6	0.3	**1.6**
51	Patulea	Alina	411									
52	Iordache	Ioan-Bogdan	412	49	2.45	40	2	10	0.5	10	0.5	**5.95**
53	Manea	Andrei-Alexandru	412	47	2.35	40	2	10	0.5	10	0.5	**5.85**

Project 2 – comming soon

- analyze video

- the plan is to release the project on week 14 (25th of May), deadline on 26/27th of June (last day) to submit your code/ results

Course structure

1. **Features and filters: low-level vision**

   Linear filters, color, texture, edge detection

2. **Grouping and fitting: mid-level vision**

   Fitting curves and lines, robust fitting, RANSAC, Hough transform, segmentation

3. **Multiple views**

   Local invariant feature and description, epipolar geometry and stereo, object instance recognition

4. **Object Recognition: high – level vision**

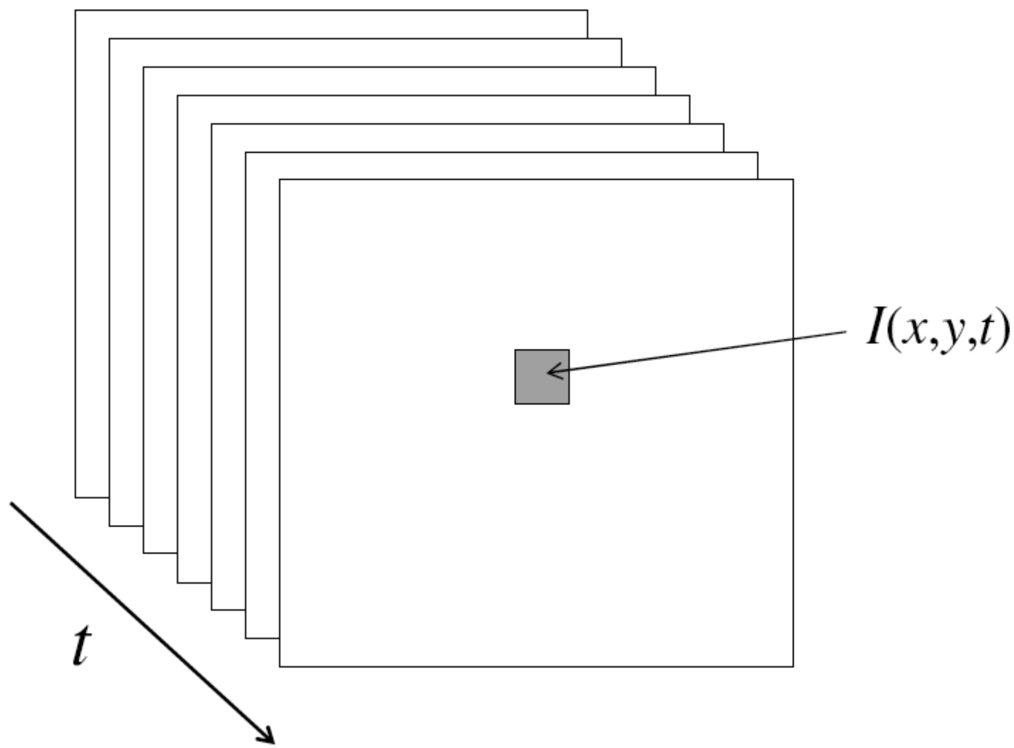
   Object classification, object detection, part based models, bovw models

5. **Video understanding**

   Object tracking, background subtraction, motion descriptors, optical flow

Video

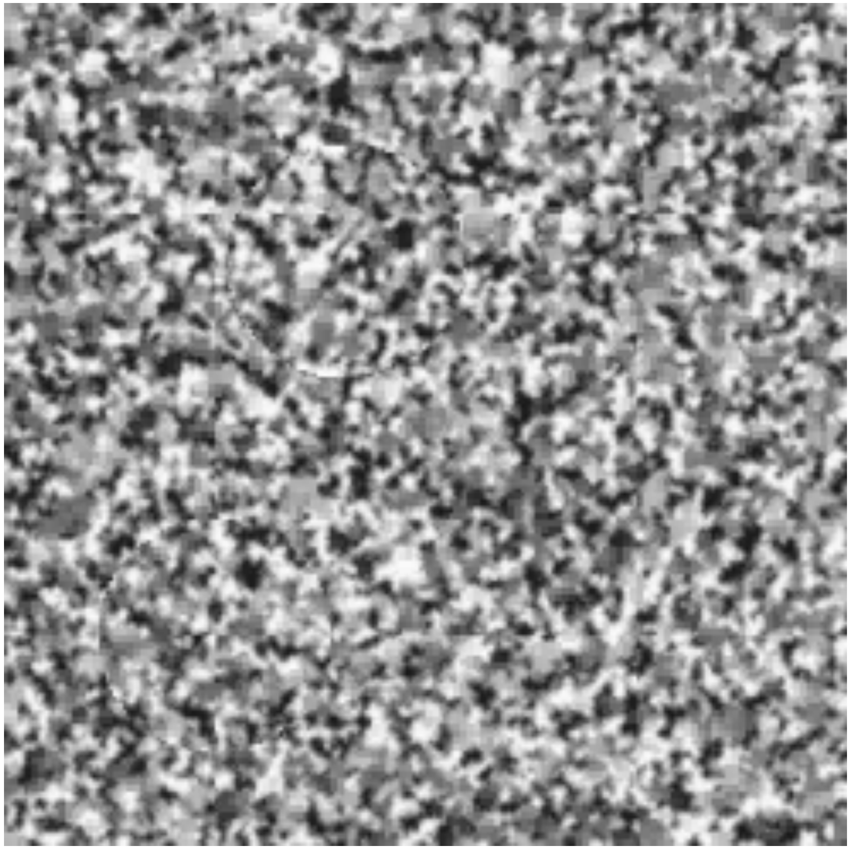
- A video is a sequence of frames captured over time
- Now our image data is a function of space (x, y) and time (t)



Optical flow and keypoint tracking

Motion is a powerful perceptual cue

- Sometimes, it is the only cue



Motion is a powerful perceptual cue

- Even "impoverished" motion data can evoke a strong percept

G. Johansson, "Visual Perception of Biological Motion and a Model For Its Analysis", *Perception and Psychophysics 14, 201-211, 1973.*

Motion is a powerful perceptual cue

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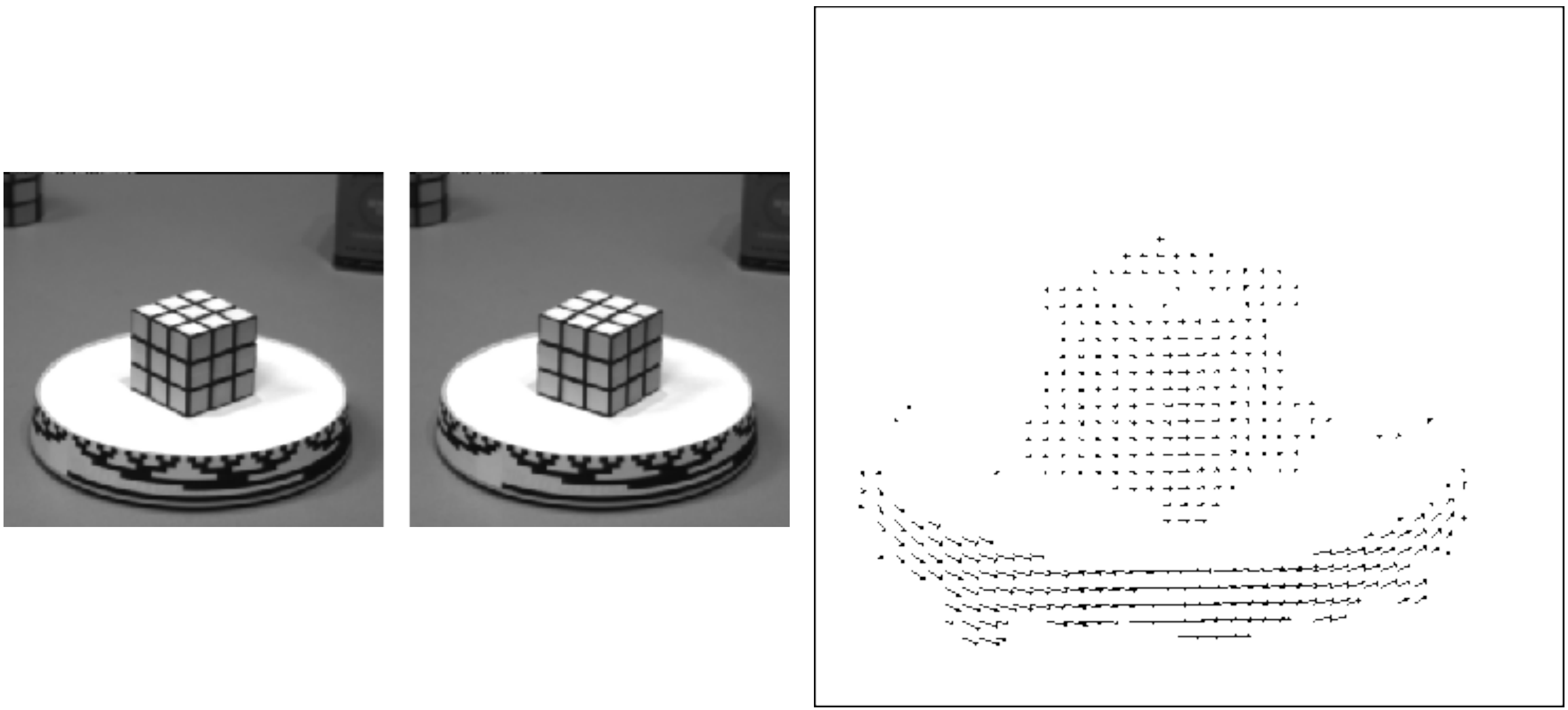
Uses of motion in computer vision

- 3D shape reconstruction
- Object segmentation
- Learning and tracking of dynamical models
- Event and activity recognition
- Self-supervised and predictive learning
- Solving project 2 ☺ (most probable)

Motion field

- The motion field is the projection of the 3D scene motion into the image



Optical flow

- **Definition**: optical flow is the *apparent* motion of brightness patterns in the image

- Ideally, optical flow would be the same as the motion field

- Have to be careful: apparent motion can be caused by lighting changes without any actual motion
  - Think of a uniform rotating sphere under fixed lighting vs. a stationary sphere under moving illumination

Apparent motion != motion field

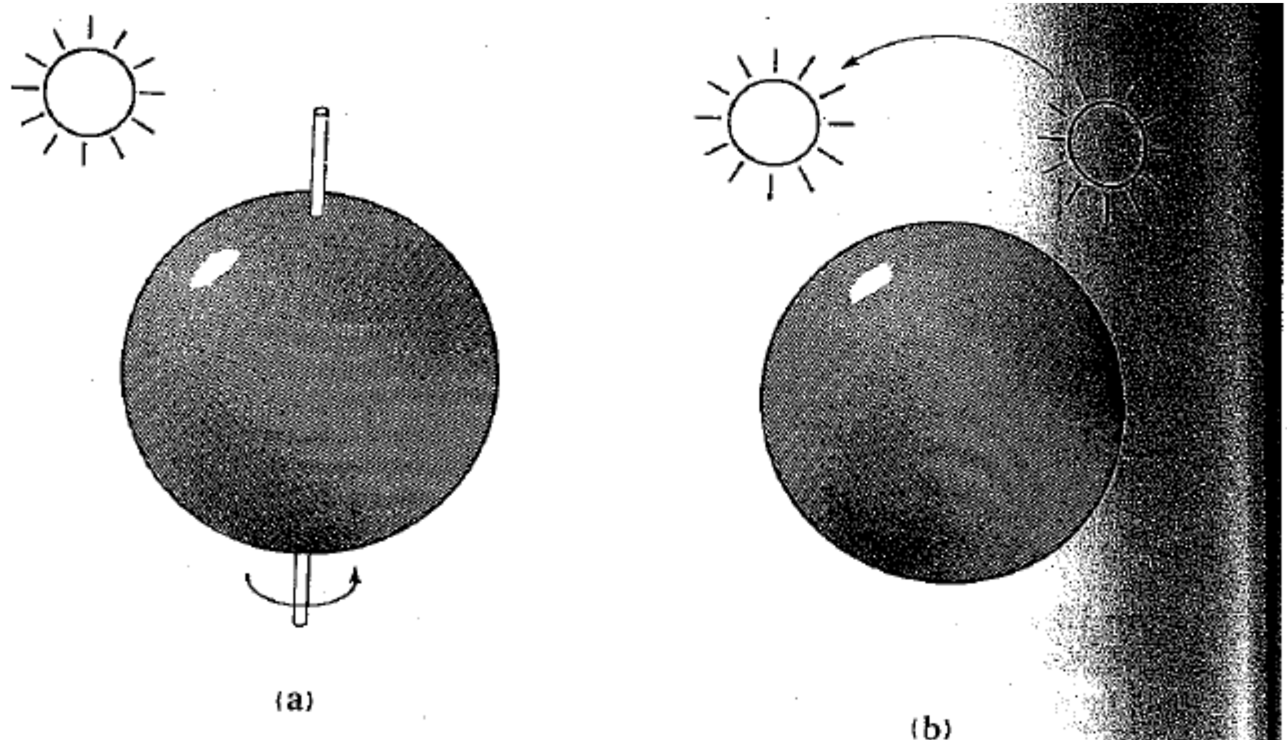


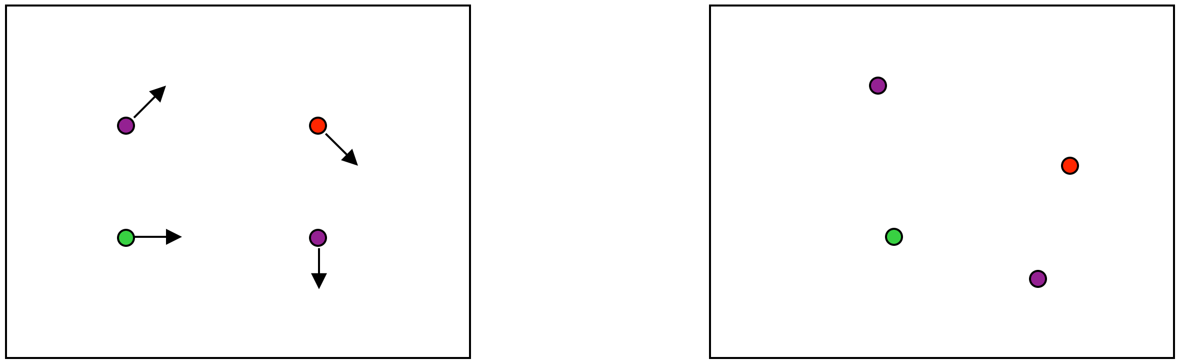
Figure 12-2. The optical flow is not always equal to the motion field. In (a) a smooth sphere is rotating under constant illumination—the image does not change, yet the motion field is nonzero. In (b) a fixed sphere is illuminated by a moving source—the shading in the image changes, yet the motion field is zero.

Apparent motion can be caused by lighting changes without any actual motion. Think of a uniform rotating sphere under fixed lighting vs. a stationary sphere under moving illumination

Optical flow

- **Definition**: optical flow is the *apparent* motion of brightness patterns in the image

Estimating optical flow

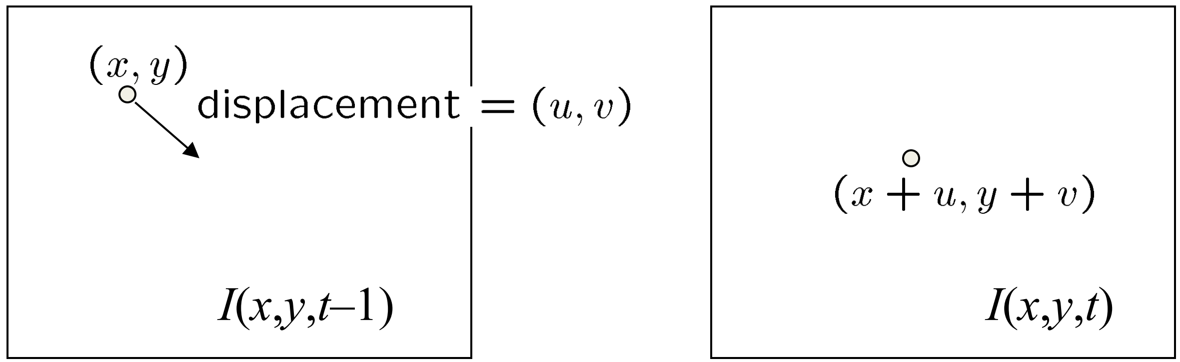


$I(x,y,t\text{-}1)$ $\quad\quad$ $I(x,y,t)$

- Given two subsequent frames, estimate the apparent motion field $u(x,y)$ and $v(x,y)$ between them

- Key assumptions
  - Brightness constancy: projection of the same point looks the same in every frame
  - Small motion: points do not move very far
  - Spatial coherence: points move like their neighbors

The brightness constancy constraint



- Brightness Constancy Equation:

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

Linearizing the right side using Taylor expansion:

$$I(x, y, t-1) \approx I(x, y, t) + I_x\, u(x, y) + I_y\, v(x, y)$$

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

The brightness constancy constraint

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

- How many equations and unknowns per pixel?
  - One equation, two unknowns

- What does this constraint mean?

$$\nabla I \cdot (u, v) + I_t = 0, \nabla I = (I_x, I_y)$$

- The component of the flow perpendicular to the gradient (i.e., parallel to the edge) is unknown!

The brightness constancy constraint

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

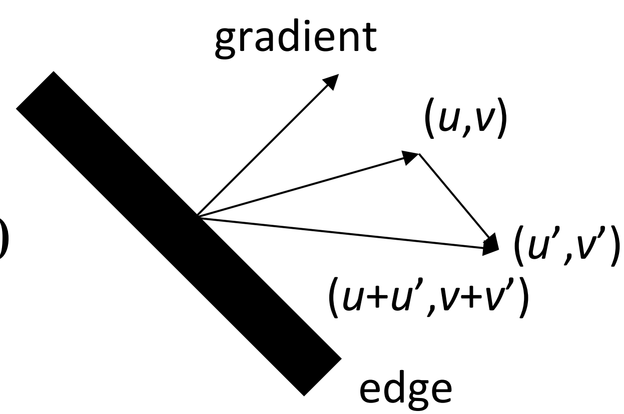
- How many equations and unknowns per pixel?
  - One equation, two unknowns

- What does this constraint mean?

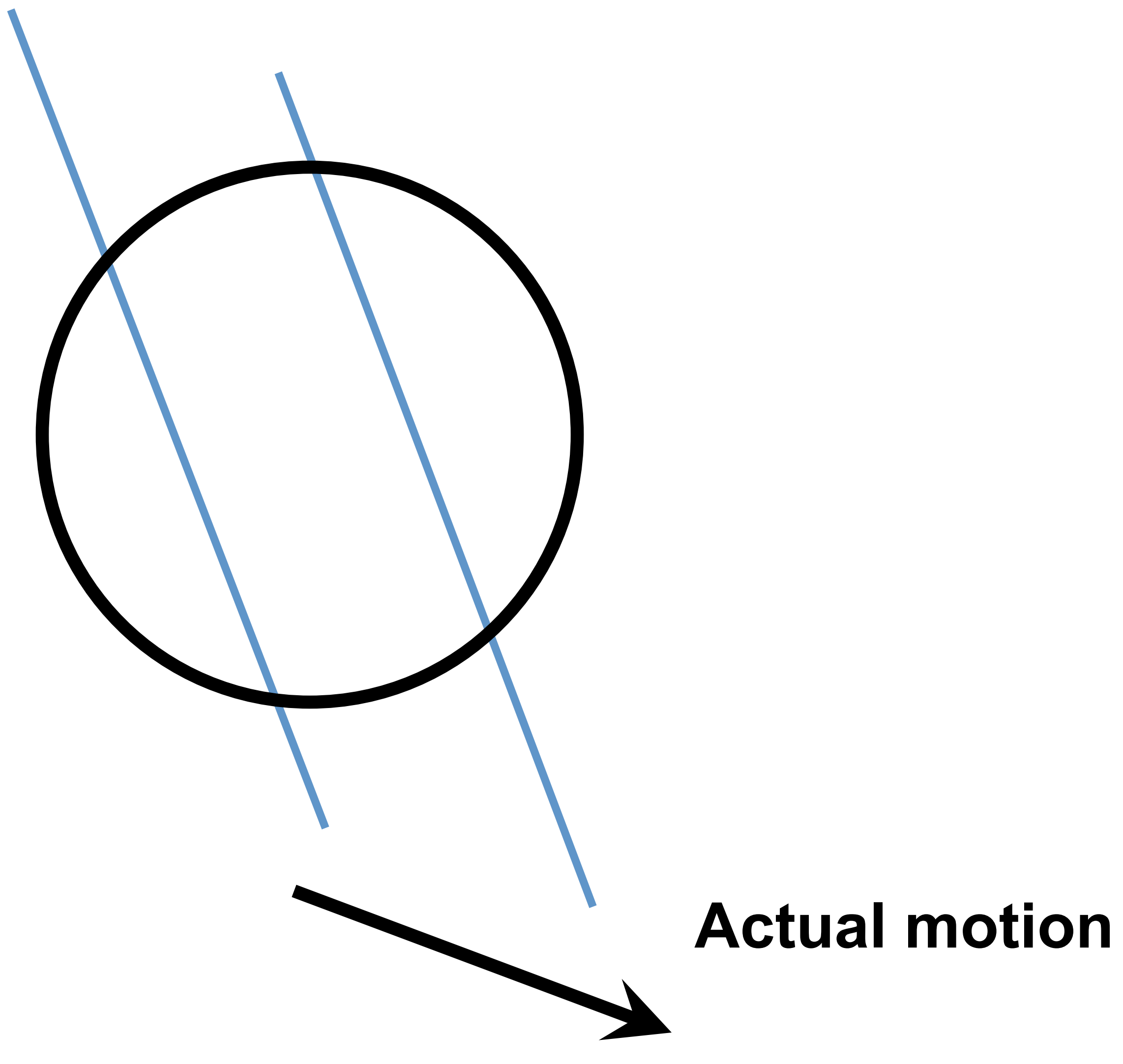
$$\nabla I \cdot (u, v) + I_t = 0$$

- The component of the flow perpendicular to the gradient (i.e., parallel to the edge) is unknown!

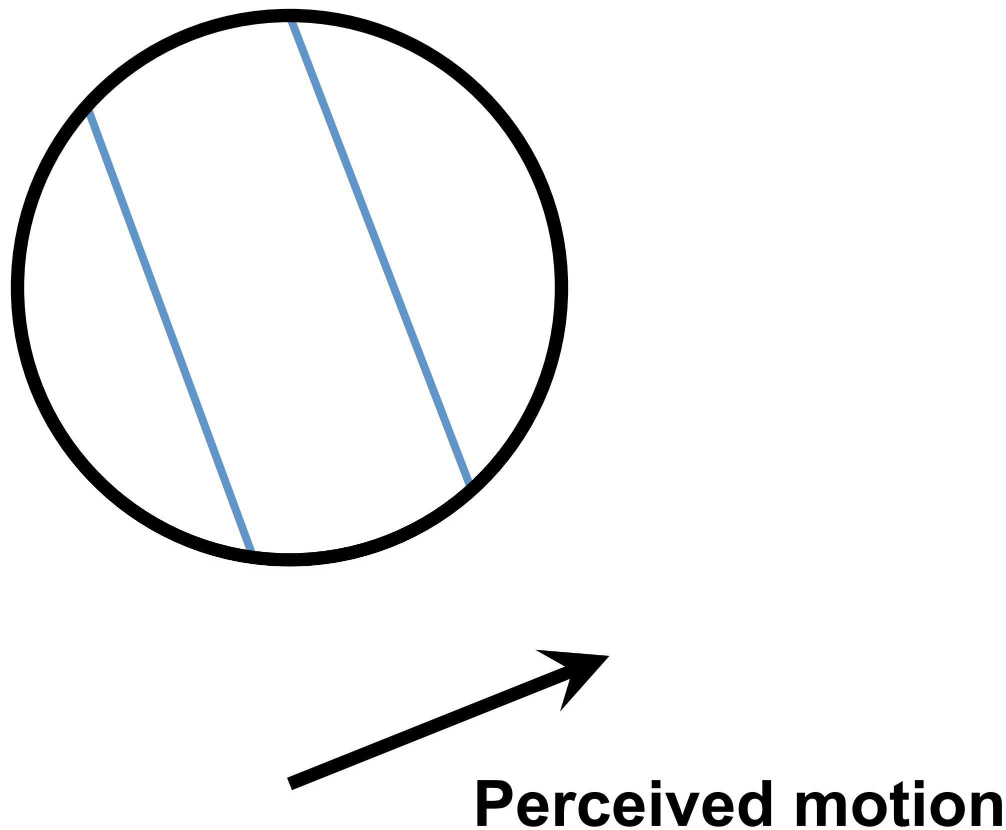
If (u, v) satisfies the equation,
so does ($u+u'$, $v+v'$) if $\nabla I \cdot (u', v') = 0$



The aperture problem



The aperture problem



The barber pole illusion

http://en.wikipedia.org/wiki/Barberpole_illusion

The barber pole illusion

http://en.wikipedia.org/wiki/Barberpole_illusion

Solving the aperture problem

- How to get more equations for a pixel?
- **Spatial coherence constraint:** assume the pixel's neighbors have the same (u,v)
  - E.g., if we use a 5x5 window, that gives us 25 equations per pixel

$$\nabla I(\mathbf{x}_i) \cdot [u, v] + I_t(\mathbf{x}_i) = 0$$

$$\begin{bmatrix} I_x(\mathbf{x}_1) & I_y(\mathbf{x}_1) \\ I_x(\mathbf{x}_2) & I_y(\mathbf{x}_2) \\ \vdots & \vdots \\ I_x(\mathbf{x}_n) & I_y(\mathbf{x}_n) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = -\begin{bmatrix} I_t(\mathbf{x}_1) \\ I_t(\mathbf{x}_2) \\ \vdots \\ I_t(\mathbf{x}_n) \end{bmatrix}$$

B. Lucas and T. Kanade. An iterative image registration technique with an application to stereo vision. In *Proceedings of the International Joint Conference on Artificial Intelligence*, pp. 674–679, 1981.

Lucas-Kanade flow

- Linear least squares problem:

$$\begin{bmatrix} I_x(\mathbf{x}_1) & I_y(\mathbf{x}_1) \\ I_x(\mathbf{x}_2) & I_y(\mathbf{x}_2) \\ \vdots & \vdots \\ I_x(\mathbf{x}_n) & I_y(\mathbf{x}_n) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} I_t(\mathbf{x}_1) \\ I_t(\mathbf{x}_2) \\ \vdots \\ I_t(\mathbf{x}_n) \end{bmatrix}$$

- When is this system solvable?

B. Lucas and T. Kanade. An iterative image registration technique with an application to stereo vision. In *Proceedings of the International Joint Conference on Artificial Intelligence*, pp. 674–679, 1981.

Lucas-Kanade flow

- Linear least squares problem:

$$\begin{bmatrix} I_x(\mathbf{x}_1) & I_y(\mathbf{x}_1) \\ I_x(\mathbf{x}_2) & I_y(\mathbf{x}_2) \\ \vdots & \vdots \\ I_x(\mathbf{x}_n) & I_y(\mathbf{x}_n) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} I_t(\mathbf{x}_1) \\ I_t(\mathbf{x}_2) \\ \vdots \\ I_t(\mathbf{x}_n) \end{bmatrix}$$

$$\underset{n\times 2}{\mathbf{A}} \; \underset{2\times 1}{\mathbf{d}} = \underset{n\times 1}{\mathbf{b}}$$

- Solution given by $(\mathbf{A}^T\mathbf{A})\mathbf{d} = \mathbf{A}^T\mathbf{b}$

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

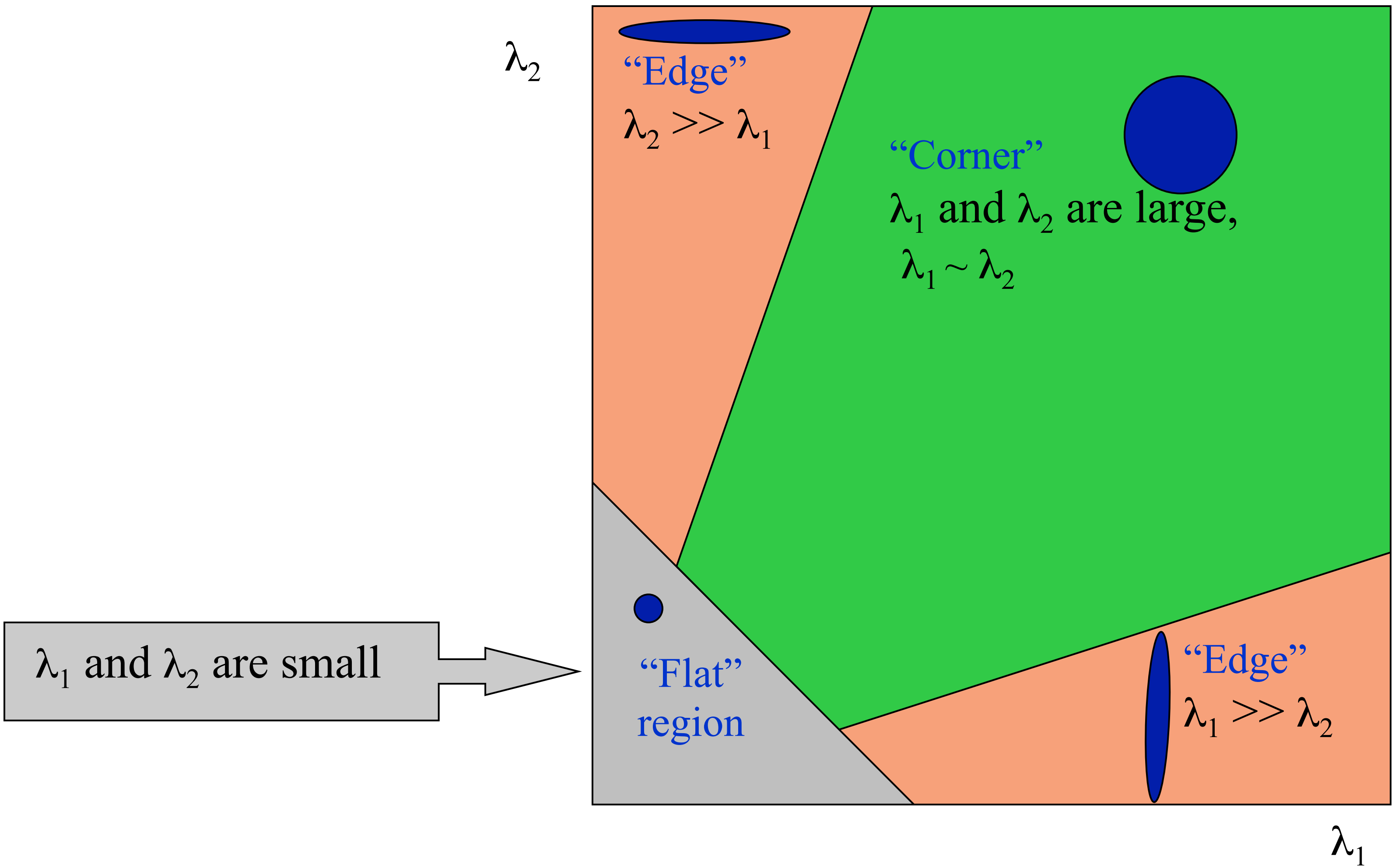
M = $A^T A$ is the second moment matrix!

(summations are over all pixels in the window)

B. Lucas and T. Kanade. An iterative image registration technique with an application to stereo vision. In *Proceedings of the International Joint Conference on Artificial Intelligence*, pp. 674–679, 1981.

Recall: second moment matrix

- Estimation of optical flow is well-conditioned precisely for regions with high "cornerness":



M = A^{T}A is the *second moment matrix* ! (Harris corner detector…)

$$A^T A = \begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} = \sum \begin{bmatrix} I_x \\ I_y \end{bmatrix} [I_x \; I_y] = \sum \nabla I (\nabla I)^T$$

- Eigenvectors and eigenvalues of A^{T}A relate to edge direction and magnitude
  - The eigenvector associated with the larger eigenvalue points in the direction of fastest intensity change
  - The other eigenvector is orthogonal to it

Low-texture region

$$\sum \nabla I (\nabla I)^T$$

– gradients have small magnitude
– small λ_1, small λ_2

Edge

$$\sum \nabla I (\nabla I)^T$$

– gradients very large or very small

– large λ_1, small λ_2

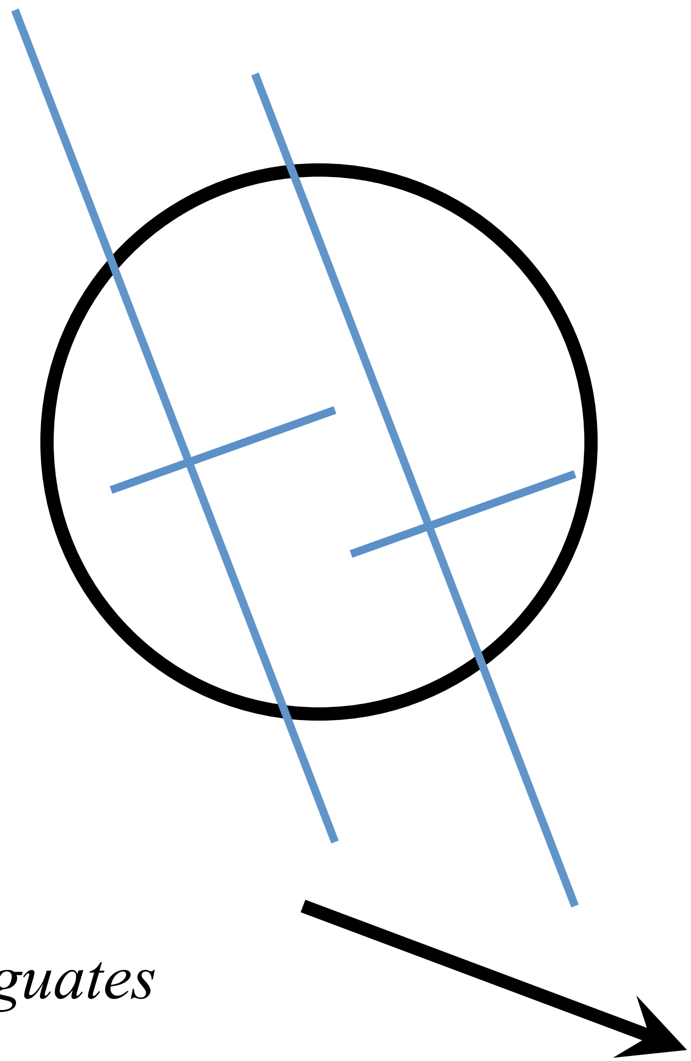
High-texture region

$$\sum \nabla I (\nabla I)^T$$

– gradients are different, large magnitudes

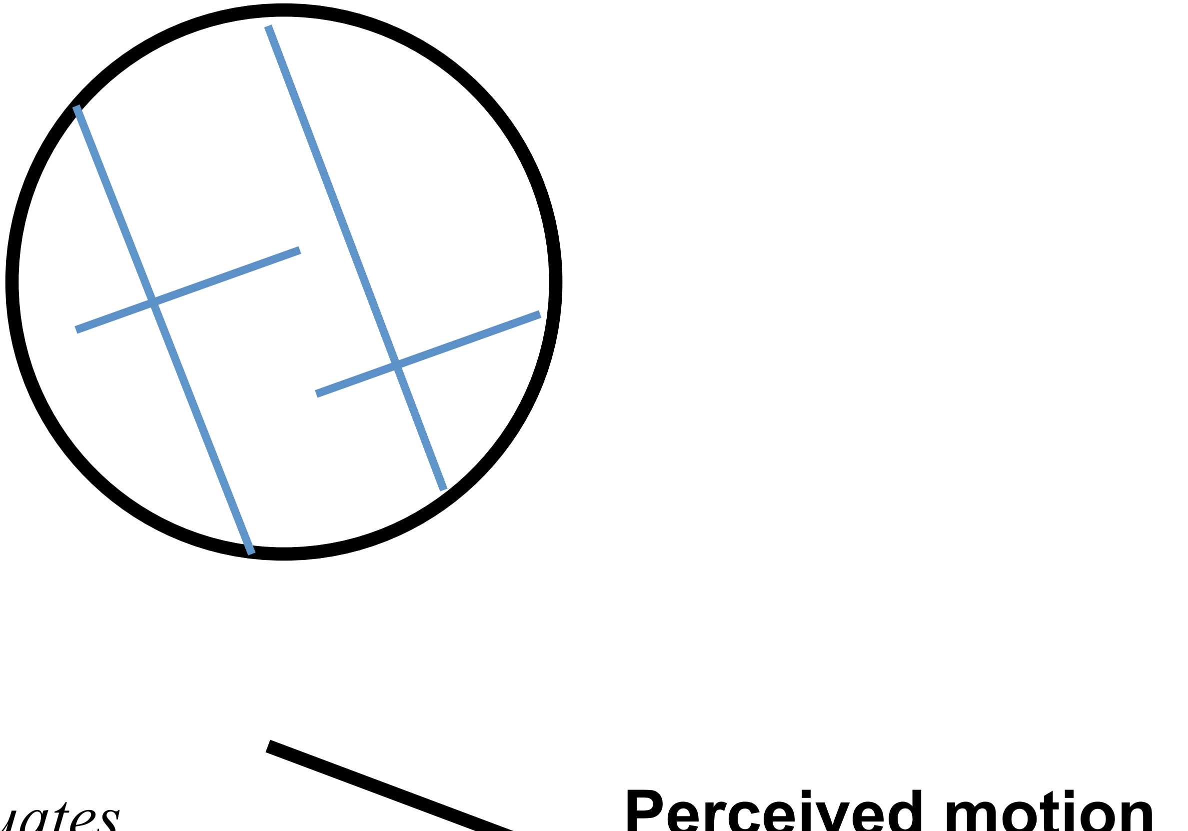
– large λ_1, large λ_2

The aperture problem resolved



Using corners disambiguates the aperture problem

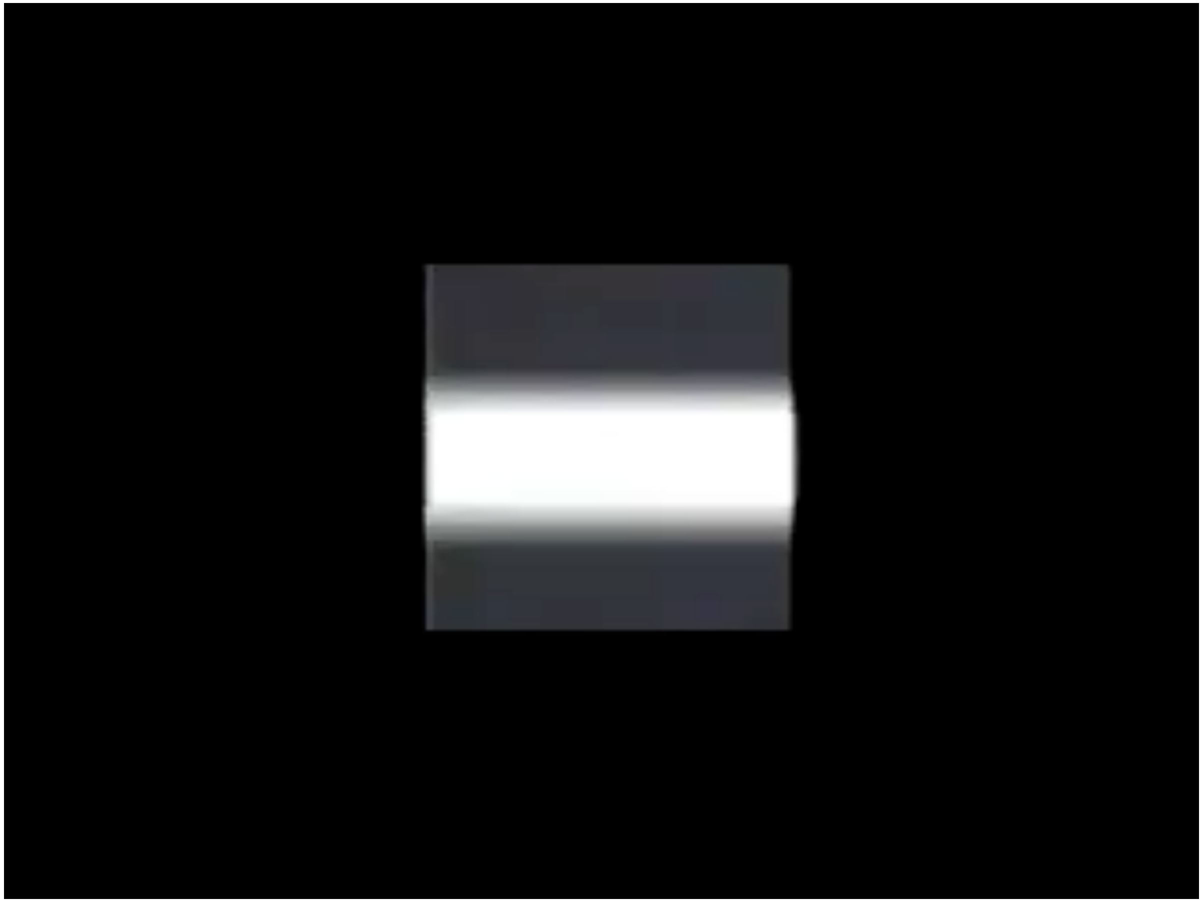
The aperture problem resolved



Using corners disambiguates the aperture problem

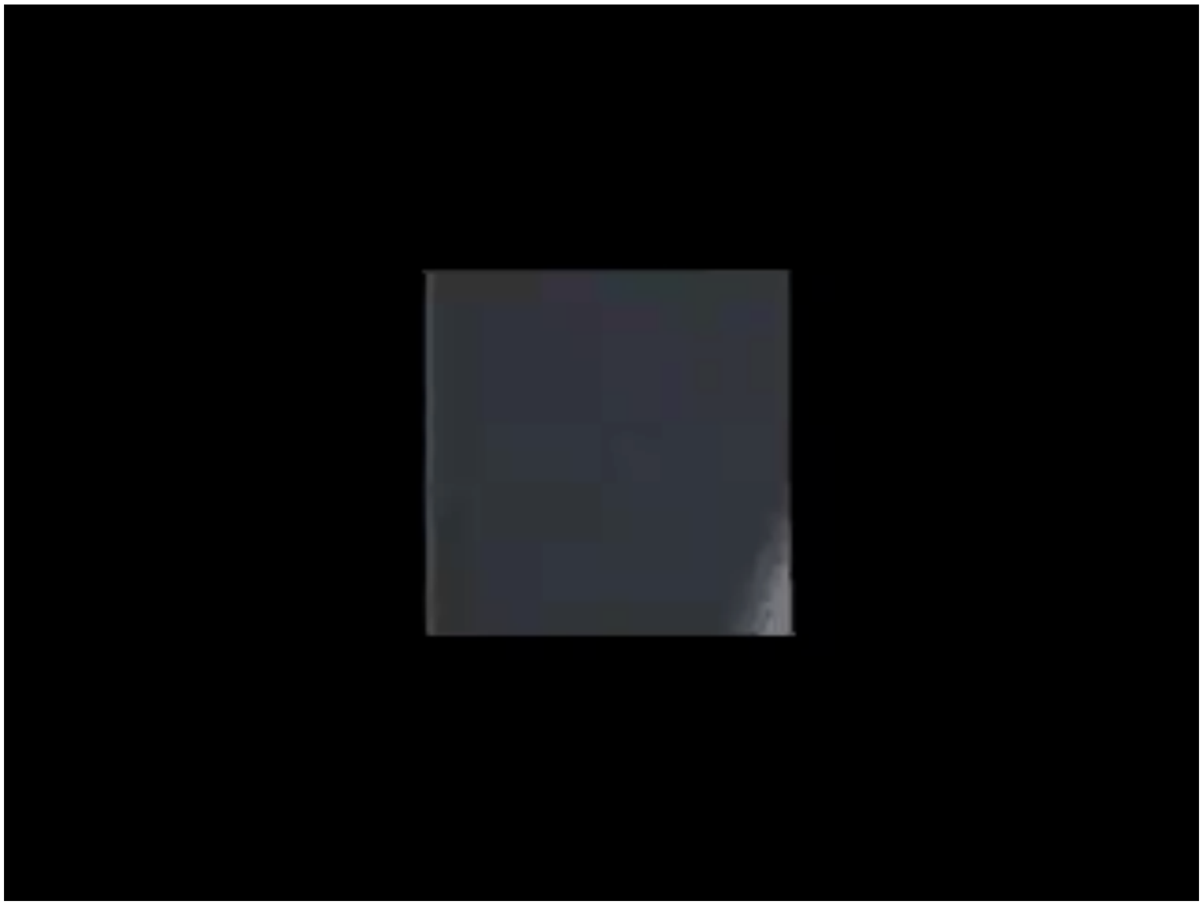
Conditions for solvability

- "Bad" case: single straight edge



Conditions for solvability

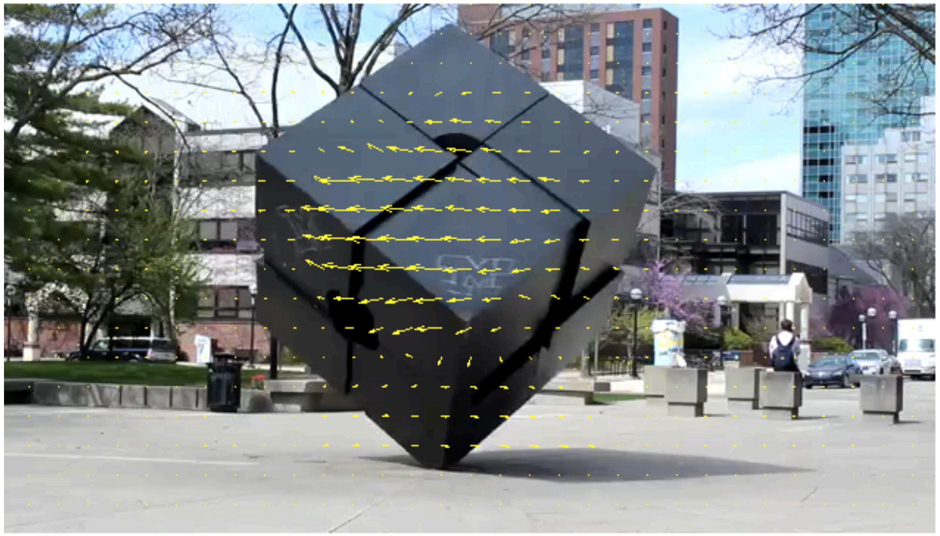
- “Good” case



Lucas-Kanade flow example

Input frames

Output



Source: [MATLAB Central File Exchange]()

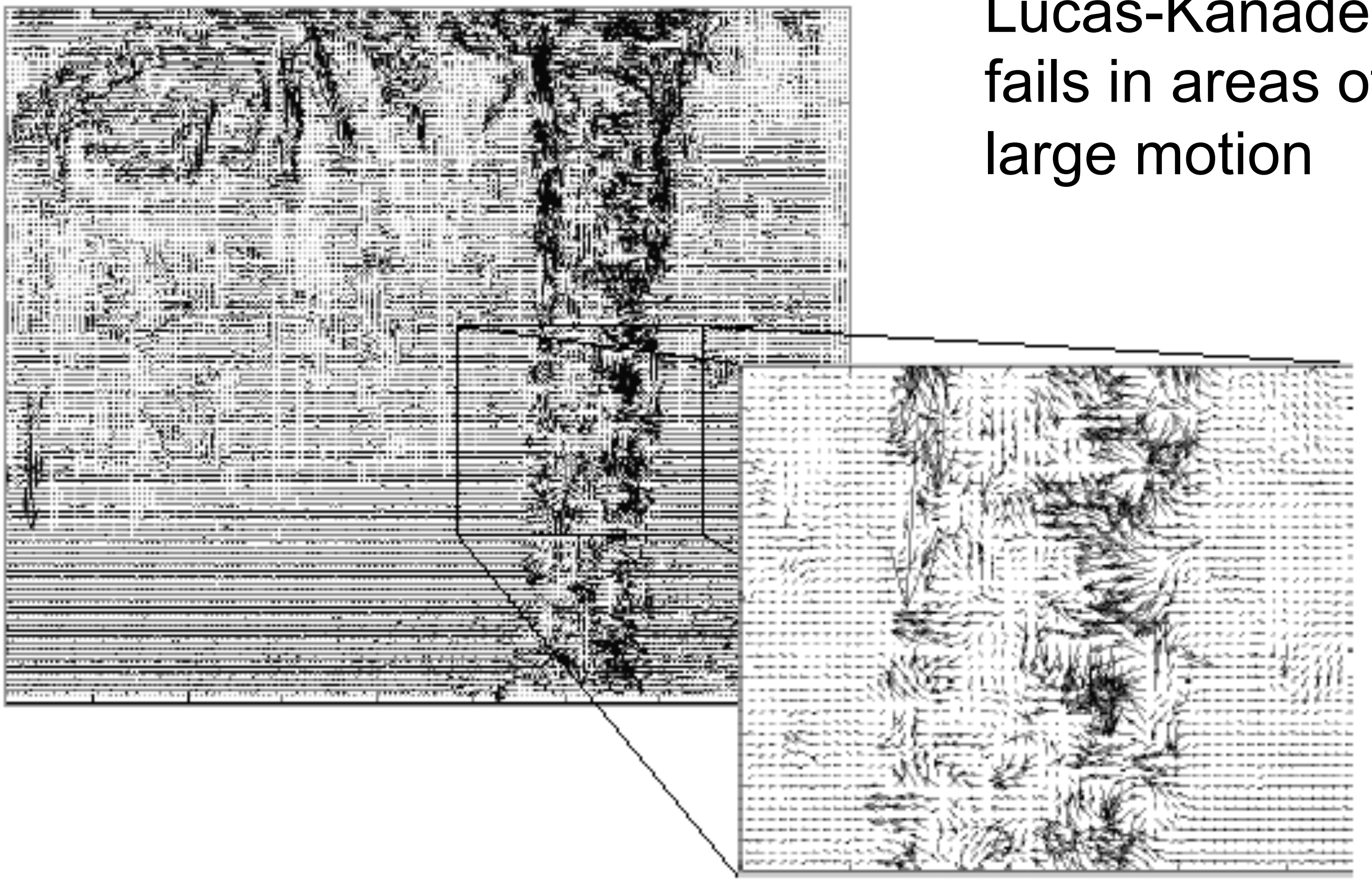
Errors in Lucas-Kanade

- The motion is large (larger than a pixel)
- A point does not move like its neighbors
- Brightness constancy does not hold

“Flower garden” example

* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

"Flower garden" example



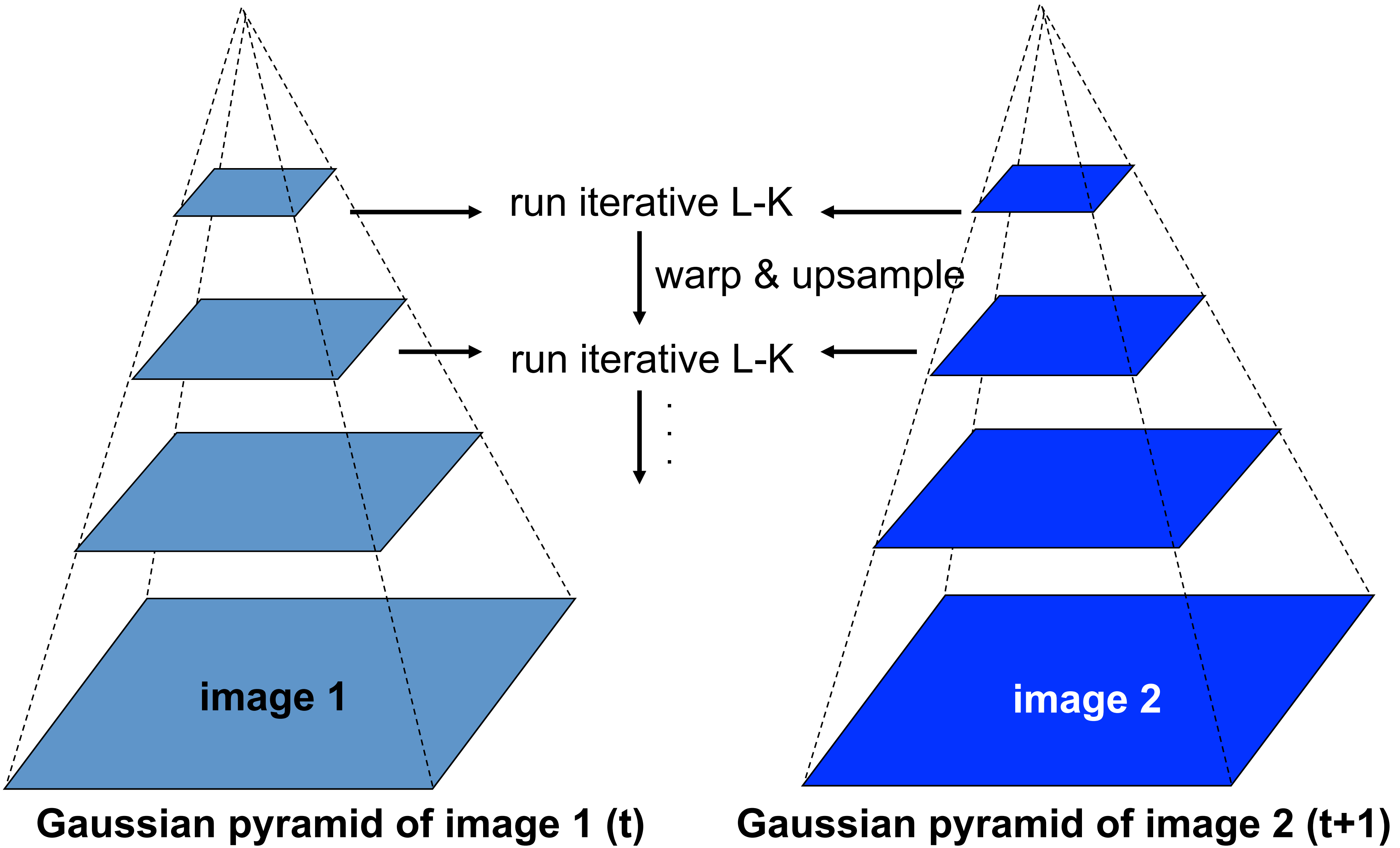
Lucas-Kanade fails in areas of large motion

* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

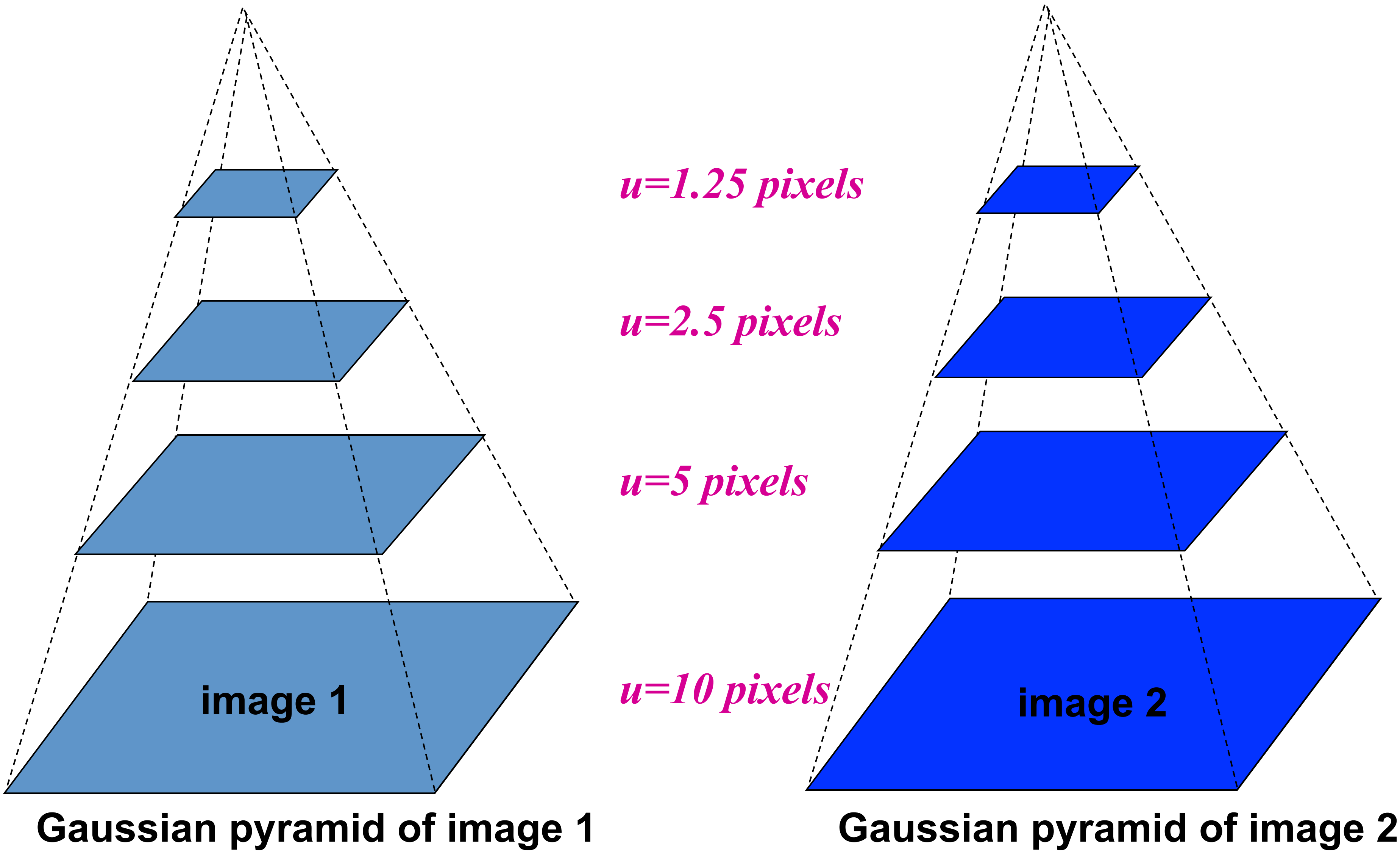
Multi-resolution Lucas Kanade Algorithm

- Compute 'simple' LK at highest level
- At level i
  - Take flow u_{i-1}, v_{i-1} from level i-1
  - bilinear interpolate it to create u_i^*, v_i^* matrices of twice resolution for level i
  - multiply u_i^*, v_i^* by 2
  - compute f_t from a block displaced by $u_i^*(x,y)$, $v_i^*(x,y)$
  - Apply LK to get $u_i'(x, y)$, $v_i'(x, y)$ (the correction in flow)
  - Add corrections u_i' v_i', *i.e.* $u_i = u_i^* + u_i'$, $v_i = v_i^* + v_i'$.

Coarse-to-fine optical flow estimation



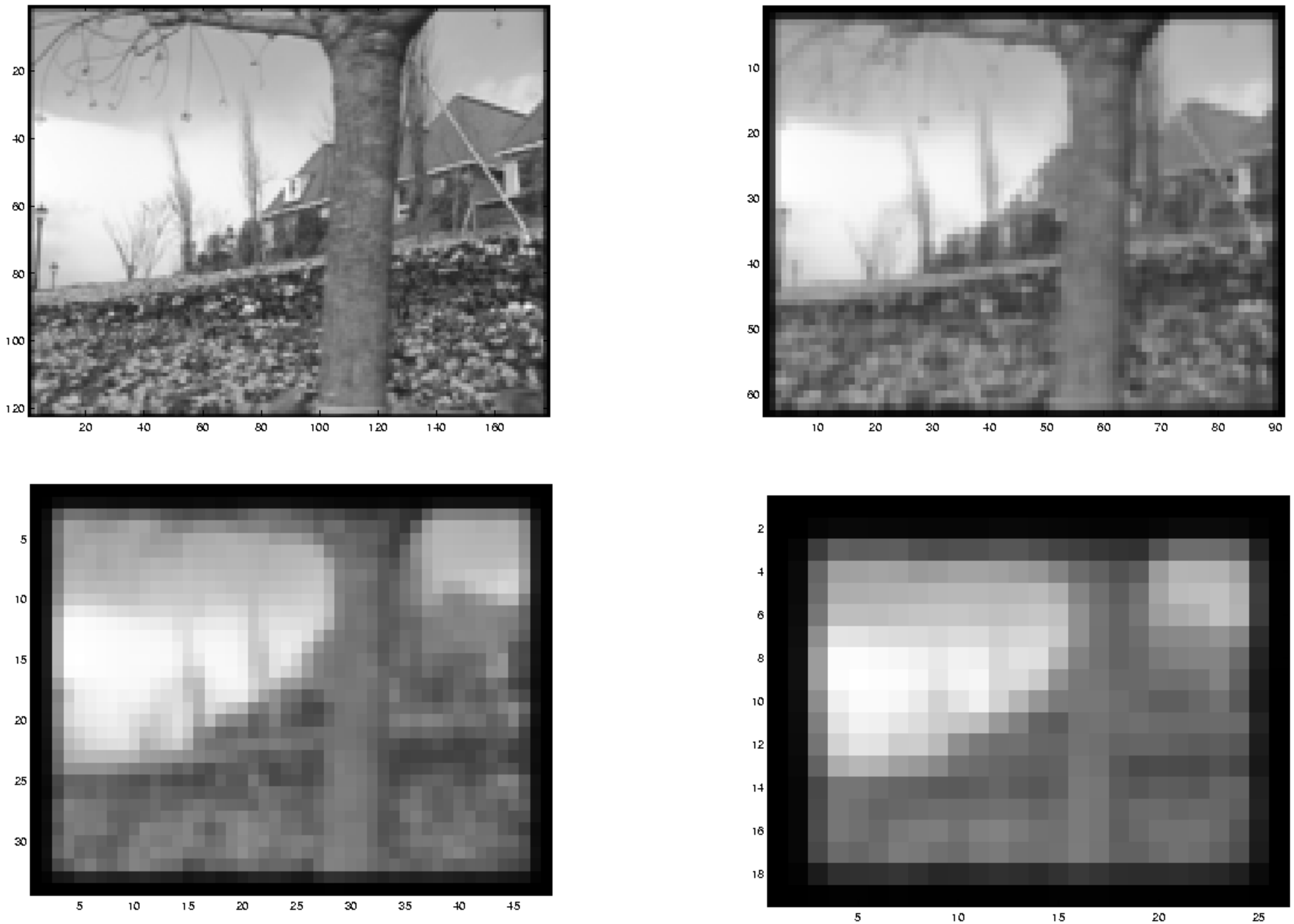
Coarse-to-fine optical flow estimation



Example

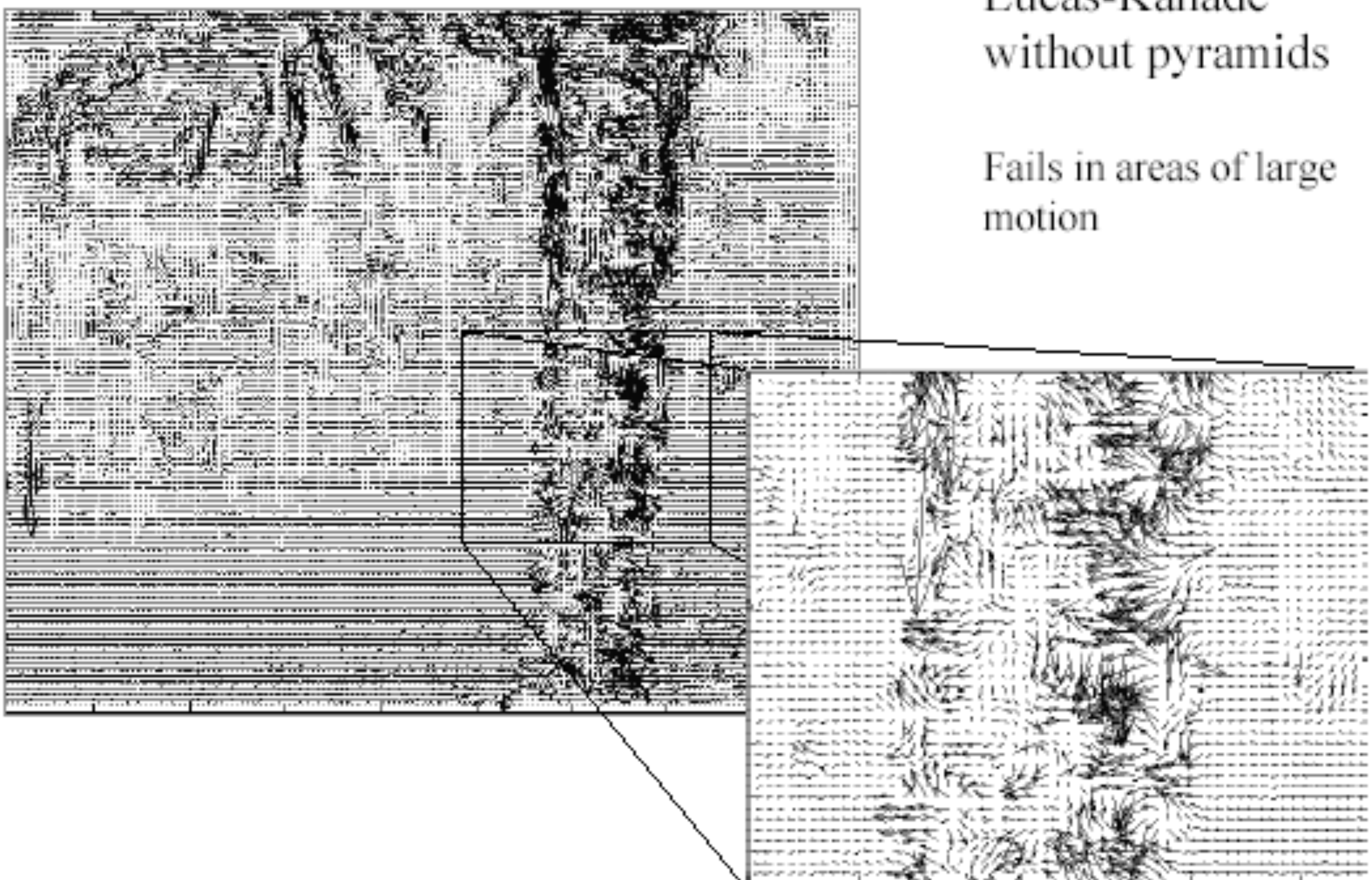
* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Multi-resolution registration



* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Optical Flow Results

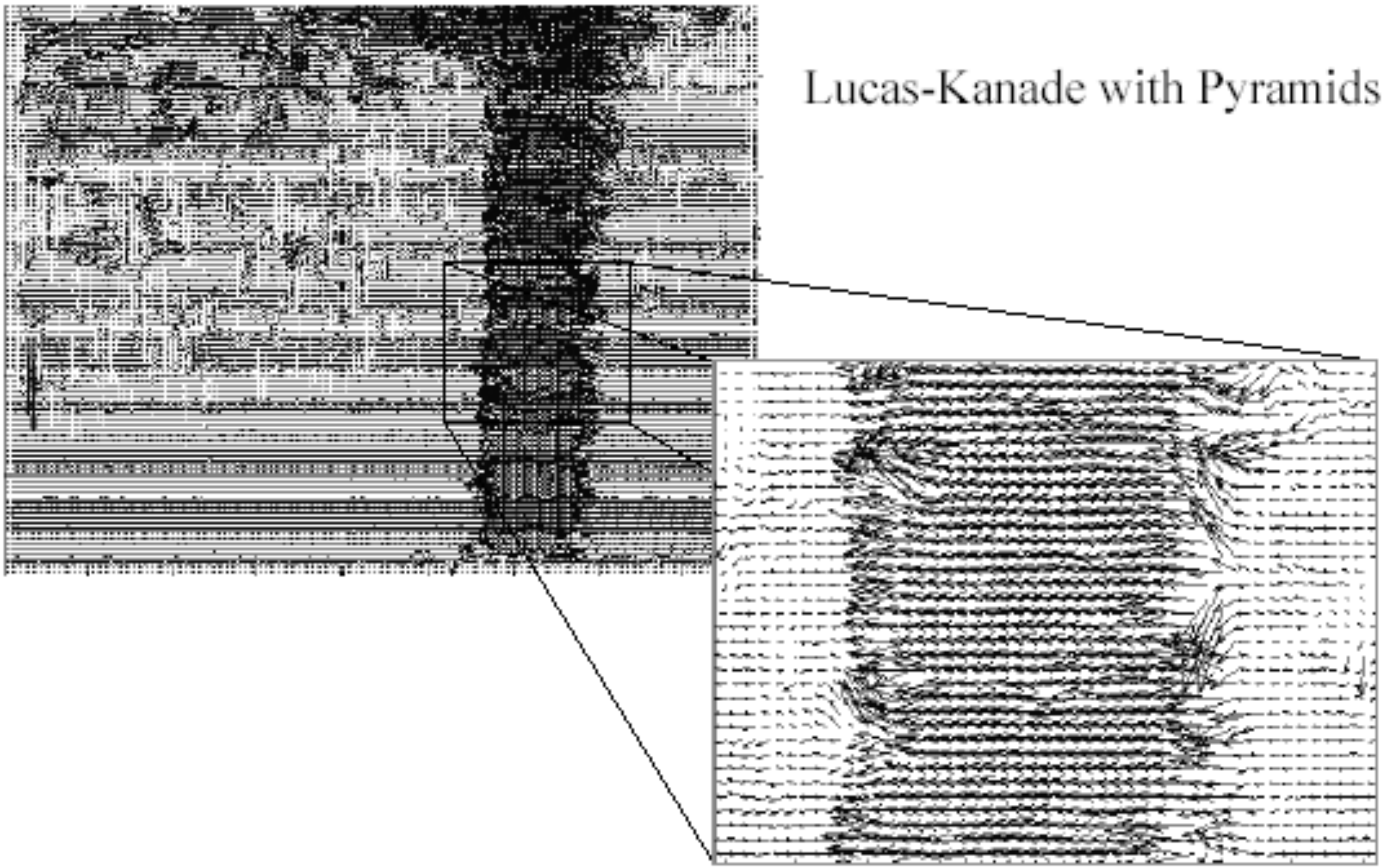


Lucas-Kanade
without pyramids

Fails in areas of large
motion

* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Optical Flow Results



Lucas-Kanade with Pyramids

* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Fixing the errors in Lucas-Kanade

- The motion is large (larger than a pixel)
  - Multi-resolution estimation, iterative refinement
  - Feature matching
- A point does not move like its neighbors
  - Motion segmentation

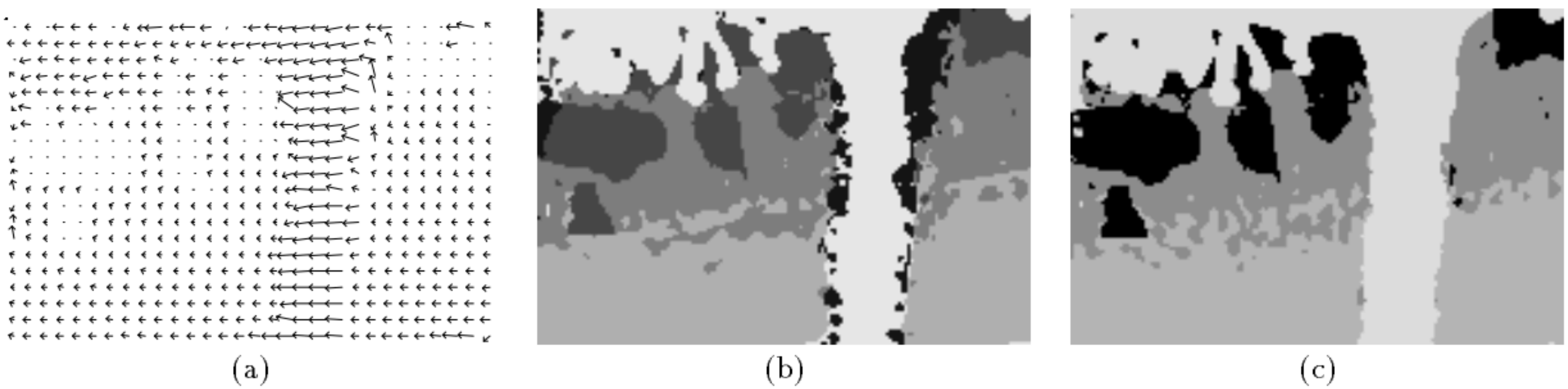


Figure 11: (a) The optic flow from multi-scale gradient method. (b) Segmentation obtained by clustering optic flow into affine motion regions. (c) Segmentation from consistency checking by image warping. Representing moving images with layers.

J. Wang and E. Adelson, Representing Moving Images with Layers, IEEE Transactions on Image Processing, 1994

Fixing the errors in Lucas-Kanade

- The motion is large (larger than a pixel)
  - Multi-resolution estimation, iterative refinement
  - Feature matching
- A point does not move like its neighbors
  - Motion segmentation
- Brightness constancy does not hold
  - Feature matching

Background subtraction

- given an image (video frame) we want to identify the ***foreground objects*** in that image.
- in most cases, objects are of interest and not the scene

$\Rightarrow$

Slide credit: Birgi Tamersoy

Background subtraction

- simple techniques can do ok with static camera
- …but hard to do perfectly

- widely used:
  - traffic monitoring (counting vehicles, detecting & tracking vehicles, pedestrians),
  - human action recognition (run, walk, jump, squat),
  - human-computer interaction
  - object tracking

Background subtraction – simple approach

Image at time t:
$I(x, y, t)$
$\Downarrow$

Background at time t:
$B(x, y, t)$
$\Downarrow$

$|$ 

$-$ 

$| > Th$

1. Estimate the background for time t.
2. Subtract the estimated background from the input frame.
3. Apply a threshold, Th, to the absolute difference to get the **foreground mask**.

Slide credit: Birgi Tamersoy

Background subtraction – frame differencing

- Background is estimated to be the previous frame. Background subtraction equation then becomes:

$$B(x, y, t) = I(x, y, t-1)$$
$$\Downarrow$$
$$|I(x, y, t) - I(x, y, t-1)| > Th$$

- Depending on the object structure, speed, frame rate and global threshold, this approach may or may **not** be useful (usually **not**).

$|$

$-$

$| > Th$

Slide credit: Birgi Tamersoy

Background subtraction – frame differencing

$Th = 25$

$Th = 50$

$Th = 100$

$Th = 200$

Slide credit: Birgi Tamersoy

Background subtraction – mean filter

- In this case the background is the mean of the previous n frames:

$$B(x,y,t) = \frac{1}{n}\sum_{i=0}^{n-1} I(x,y,t-i)$$
$$\Downarrow$$
$$|I(x,y,t) - \frac{1}{n}\sum_{i=0}^{n-1} I(x,y,t-i)| > Th$$

- For $n = 10$:

Estimated Background

Foreground Mask

Slide credit: Birgi Tamersoy

Background subtraction – median filter

- Assuming that the background is more likely to appear in a scene, we can use the median of the previous n frames as the background model:

$$B(x, y, t) = median\{I(x, y, t - i)\}$$
$$\Downarrow$$
$$|I(x, y, t) - median\{I(x, y, t - i)\}| > Th \text{ where } i \in \{0, \ldots, n - 1\}.$$

- For $n = 10$:

Estimated Background

Foreground Mask

Slide credit: Birgi Tamersoy

Average/Median Image

Alyosha Efros, CMU

Background Subtraction

 - 

= 

Alyosha Efros, CMU

Pros and cons

Advantages:

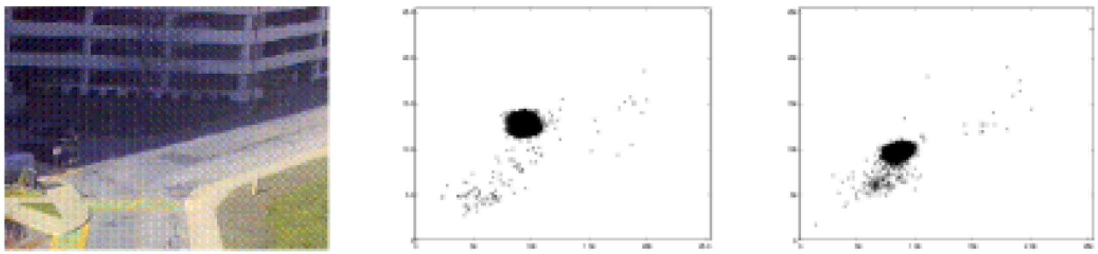
- Extremely easy to implement and use!
- All pretty fast.
- Corresponding background models need not be constant, they change over time.

Disadvantages:

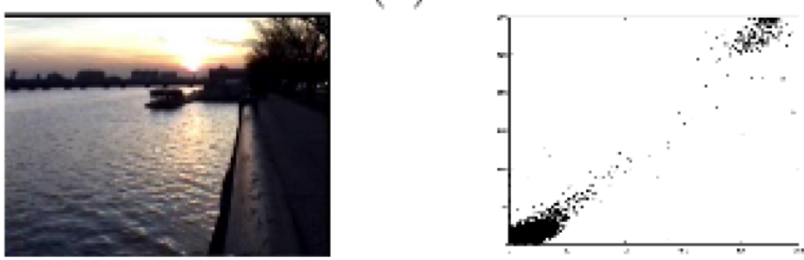
- Accuracy of frame differencing depends on object speed and frame rate
- Median background model: relatively high memory requirements.
- Setting global threshold Th…

When will this basic approach fail?

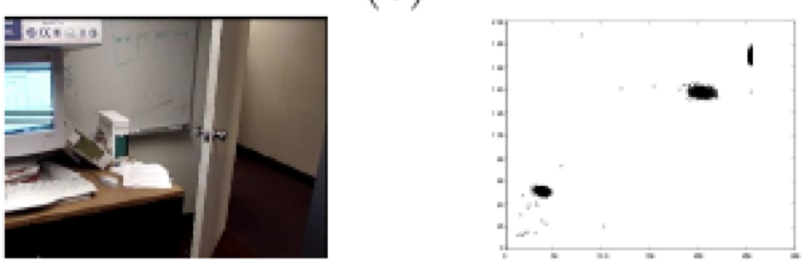
Background mixture models



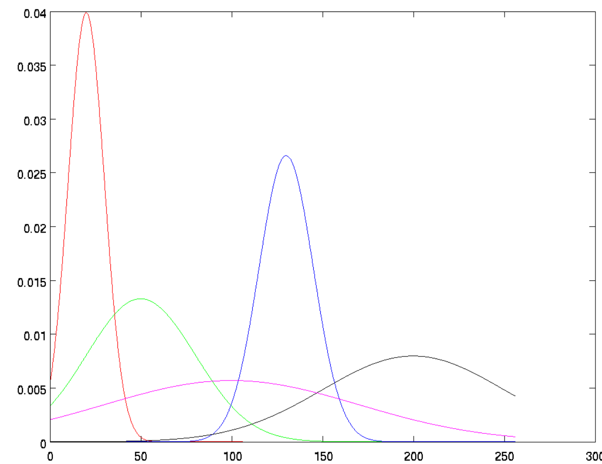
(a)



(b)



(c)



Idea: model each background pixel with a *mixture* of Gaussians; update its parameters over time.

- Adaptive Background Mixture Models for Real-Time Tracking, Chris Stauffer & W.E.L. Grimson