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Lecture Outline

1. Videos and motion
2. Differencing
3. Background subtraction
4. Optical flow
5. Applications of optical flow
6. Tracking
7. Active Shape Models
8. Structure from Motion

Importance

- Perceiving, understanding and predicting motion is an important part of our daily lives
- We want our machines to be able to do the same

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Videos over images

- Scene is continuously changing in a dynamic environment
- Images are not able to capture these dynamics
- In videos, we have sequence of frames
- By modeling the motion or variation between two consecutive frames, we can infer a lot of new information
- There are different type of approaches:
  - Background subtraction
  - Optical flow
  - Particle filter
  - Kalman filter etc.

Human and motion

- Human are very good at analyzing motion
- Motion is the first thing we attend to in the visual scene
- This has been very useful in human evolution and survival in past.
- Hence, human brain is hardwired to perceive motion, which lead to some optical illusions.

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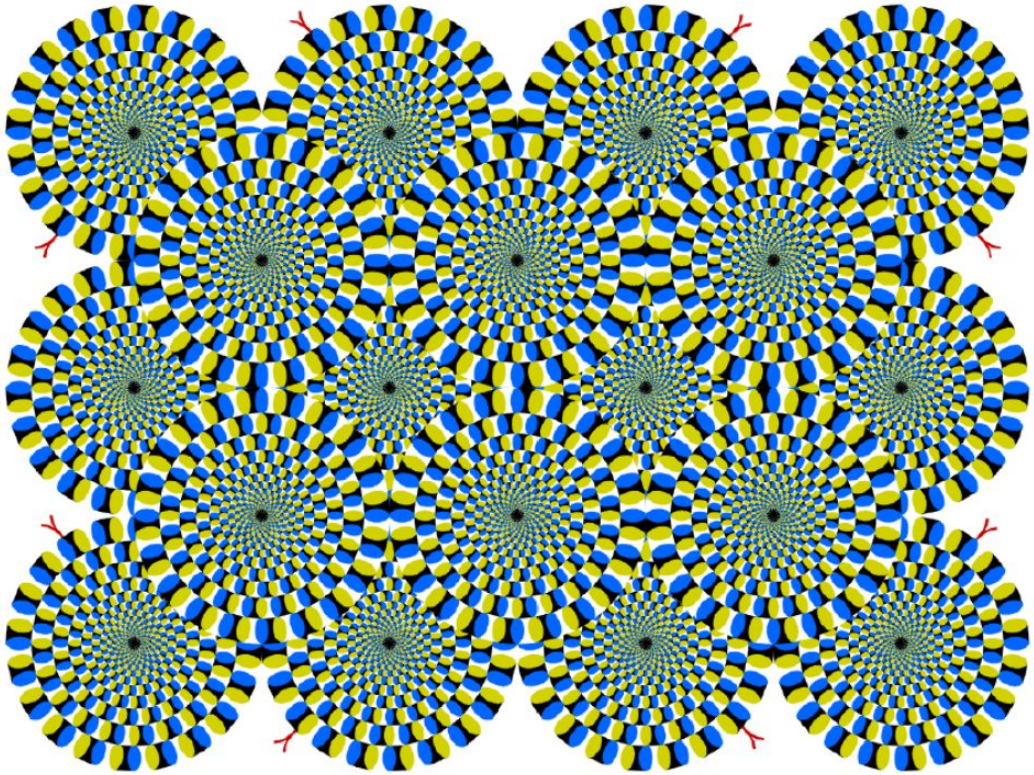
Motion from a static picture!

Focus on the image for a couple of seconds and you will see!

This is called “rotating snakes”



The causes of motion

- Changes in the scene can be observed because of:
  - moving camera
  - moving objects
  - varying lighting conditions
- All these factors contribute to the perceived motion in the image plane and can generate ambiguity about cause of the motion
- Ideally we would want to reverse-engineer the structure and dynamics of the scene (geometry, reflectance, lighting, camera egomotion and parameters) -> intractable!
- In practice, we make assumptions on reflectance of surfaces, motion(slow, smooth), lighting (fixed or slow changing), etc

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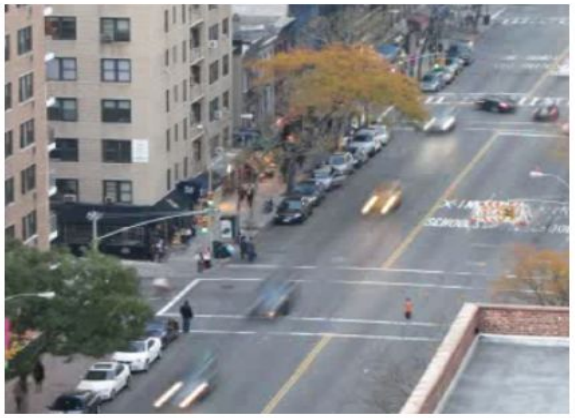
Four scenarios for motion estimation

static camera, moving scene

moving camera, static scene

moving camera AND scene



static camera, moving scene AND lights

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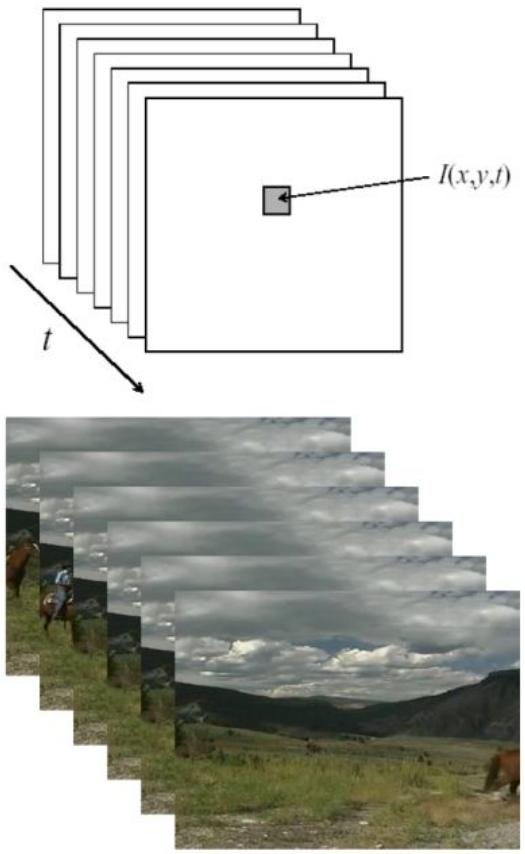
Video and motion



- A video is sequence of images
- Hence it is a spatio-temporal volume
- Each point in volume (pixel) can be represented as I(x,y,t)
- x,y are spatial dimensions and t is temporal dimension
- time between two consecutive frames: frame interval
- frame rate: inverse of the frame interval

Differencing

- Differencing uses motion in frames to estimate the foreground and the background
- Useful in segmenting out object where objects of interest are in motion

Differencing

- If any pixel in current frame of video is represented by I(x,y,t)
- Then same pixel in previous frame will be: I(x,y,t-1)
- In differencing, we subtract previous frame from current frame and take the magnitude. Then threshold that magnitude matrix.
  - Difference matrix= | I(x,y,t) - I(x,y,t-1)|
  - Apply thresholding

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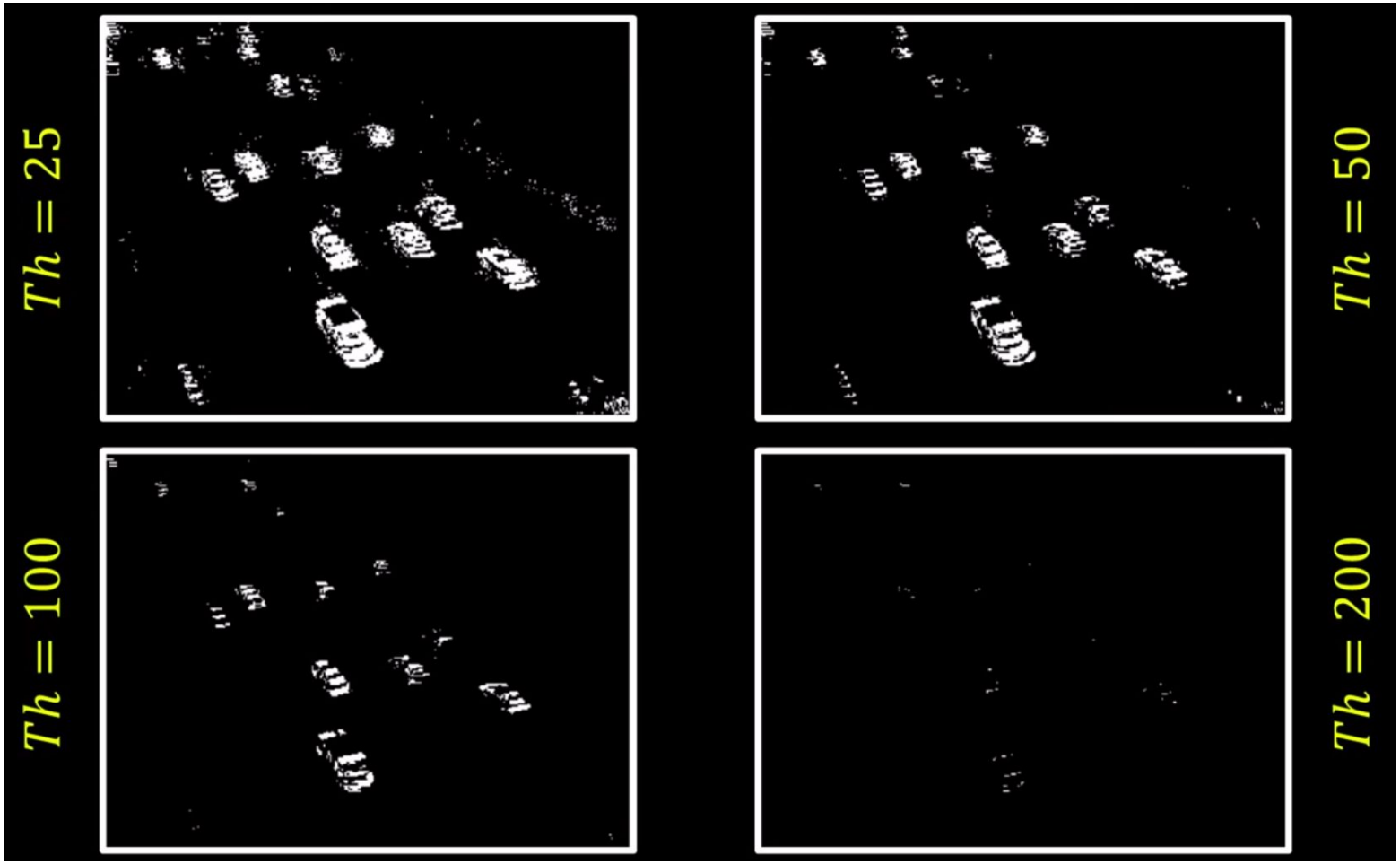
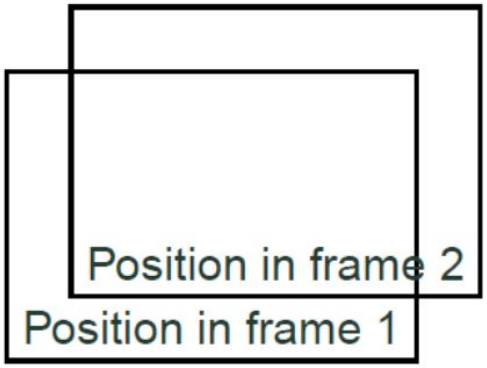
Results of Differencing



Issues with differencing

- Grey levels differ in locations where the vehicle was in the last image and where it is in the current image
- as a result, the difference image contains a double view of each vehicle
- in the example, the vehicles looks bigger than it actually is
- Secondly, if object are big and have uniform surface then differencing will not give value in the middle of surface.



Background subtraction

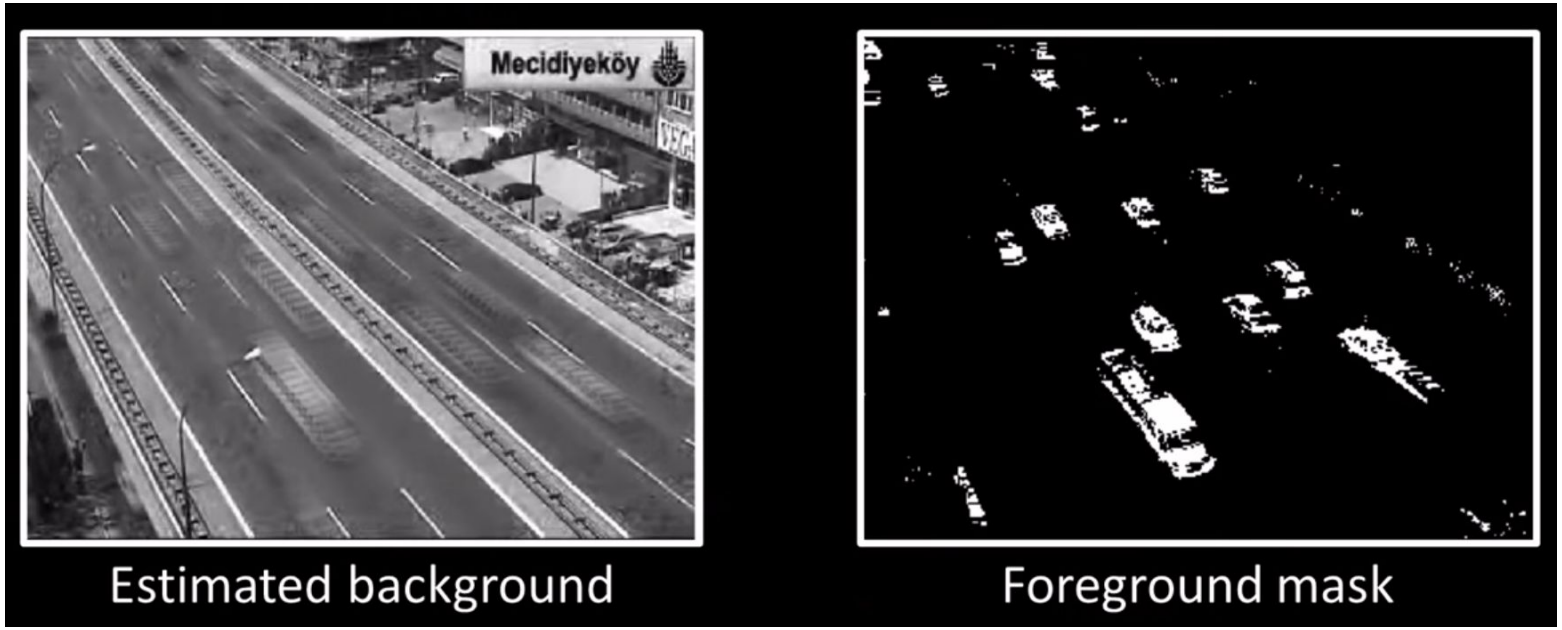
- Compares an observed image with a ‘reference’ image,
- Reference image: an estimate of what the image would look like if it contained no objects of interest
- create reference image (stationary background) by averaging a long sequence
- a significant difference between observed and reference images indicates the location of the object(s) of interest, after thresholding.

Background subtraction algorithm

- create an image of the stationary background by averaging a long sequence
- compute the difference with the background image
- apply appropriate threshold

Background subtraction

- the sequence now looks cleaner, though there is still some noise
- there are no ‘double views’



Background subtraction- Issues and challenges

- motion detection of this kind works only if camera is stationary and objects move against fixed background
- background subtraction requires acquiring a good reference image
- A good reference image can require at least 1000 frames for averaging
- this is sensitive to illumination conditions (night vs day or cloudy day versus sunny day), shadows, amount of other objects Moving etc.

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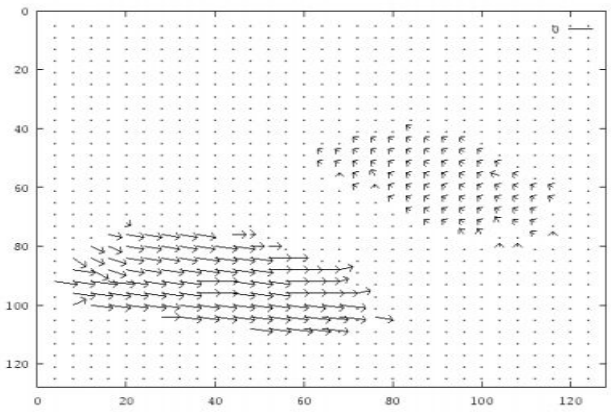
Optical Flow

- Optical flow is represented in term of motion vector (u,v)
- Which is image displacement in x and y directions between two consecutive frames

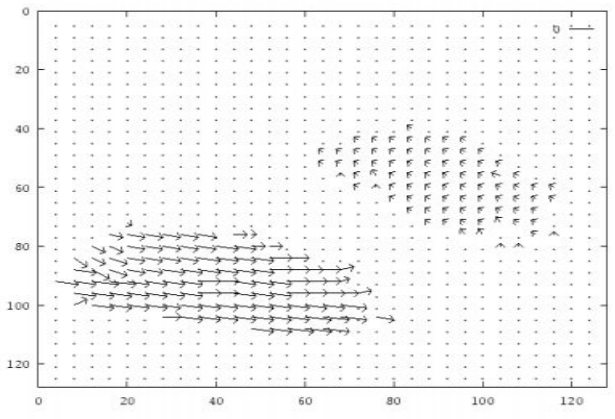


Optical flow computation

given intensity values of the image sequence I(x, y, t) we want:

$$\mathbf{u}(x,y) = [u(x,y), v(x,y)], \qquad u = \frac{dx}{dt}, v = \frac{dy}{dt}$$

field of arrows, each proportional to the amount of pixel motion



Taylor Series

A Taylor series is a series expansion of a function about a point.

A one dimensional Taylor series is an expansion of a real function f(x) about a point x=a is given by:

$$f(x) = f(a) + f'(a)(x-a) + \frac{f''(a)}{2!}(x-a)^2 + \frac{f^{(3)}(a)}{3!}(x-a)^3 + \ldots + \frac{f^{(n)}(a)}{n!}(x-a)^n + \ldots.$$

Optical flow

- Brightness constancy assumption:
  - image intensity in a small region remains the same, the region's location may change
  - in other words, only location of pixel changes with time but the brightness of each scene point remains same.
  - So the next time frame can be represented as:

$$f(x, y, t) = f(x + dx, y + dy, t + dt)$$

- The equation can be represented in term of taylor series as:

$$f(x, y, t) = f(x, y, t) + \frac{\partial f}{\partial x}(x + dx - x) + \frac{\partial f}{\partial y}(y + dy - y) + \frac{\partial f}{\partial t}(t + dt - t)$$

Optical flow

- If we consider motion to be slow and smooth in the previous equation.
- Then we can equate derivative to zero as change is x and y are negligible.

$$0 = f_x dx + f_y dy + f_t dt$$

$$0 = f_x \frac{dx}{dt} + f_y \frac{dy}{dt} + f_t \frac{dt}{dt}$$

$$0 = f_x u + f_y v + f_t$$

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Derivative Masks (Roberts)

Derivative masks for:

x direction

$$\begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix} \text{first image}$$

$$\begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix} \text{second image}$$

f_x

y direction

$$\begin{bmatrix} -1 & -1 \\ 1 & 1 \end{bmatrix} \text{first image}$$

$$\begin{bmatrix} -1 & -1 \\ 1 & 1 \end{bmatrix} \text{second image}$$

f_y

t direction

$$\begin{bmatrix} -1 & -1 \\ -1 & -1 \end{bmatrix} \text{first image}$$

$$\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \text{second image}$$

f_t

Apply masks on first and second image and add to get the value of f_x, f_y and f_t

Horn & Schunck approach

$$\iint \{(f_x u + f_y v + f_t)^2 + \lambda(u_x^2 + u_y^2 + v_x^2 + v_y^2)\} dx dy$$

Brightness constancy

Smoothness constraint

Using variational calculus, we can rewrite above equation as:

$$(f_x u + f_y v + f_t) f_x + \lambda(\Delta^2 u) = 0$$

$$(f_x u + f_y v + f_t) f_y + \lambda((\Delta^2 v) = 0$$

$$\Delta^2 u = u_{xx} + u_{yy}$$

Horn & Schunck approach

$$(f_x u + f_y v + f_t) f_x + \lambda(\Delta^2 u) = 0$$
$$(f_x u + f_y v + f_t) f_y + \lambda((\Delta^2 v) = 0$$

Using variational calculus

$$u = u_{av} - f_x \frac{P}{D}$$
$$v = v_{av} - f_y \frac{P}{D}$$

Rewriting the above equation

$$(f_x u + f_y v + f_t) f_x + \lambda(u - u_{av}) = 0$$
$$(f_x u + f_y v + f_t) f_y + \lambda((v - v_{av}) = 0$$

$$P = f_x u_{av} + f_y v_{av} + f_t$$
$$D = \lambda + f_x^2 + f_y^2$$

Algorithm to calculate optical flow

- k=0
- Initialize $u^K \quad v^K$
- Repeat until some error measure is satisfied (converges)

$$u = u_{av} - f_x \frac{P}{D}$$

$$v = v_{av} - f_y \frac{P}{D}$$

$$P = f_x u_{av} + f_y v_{av} + f_t$$

$$D = \lambda + f_x^2 + f_y^2$$

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Example of optical flow

https://www.youtube.com/watch?v=ysGM3CfBVpU

https://www.youtube.com/watch?v=LjjJQ81RbX0

Lucas & Kanade Method

The standard optical flow equation is: $f_x u + f_y v = -f_t$

Now if we consider the assumption that the neighbourhood of a pixel have same optical flow; then, 3x3 neighbourhood can be represented as:

$$f_{x1} u + f_{y1} v = -f_{t1}$$

$$\vdots$$

$$f_{x9} u + f_{y9} v = -f_{t9}$$

Lucas & Kanade Method

Another way to solve the optical flow equation is to use least square fit.

Assumption remain the same that neighbourhood has same optical flow vectors.

$$\min \sum_i (f_{xi}u + f_{yi}v + f_t)^2$$

$$\frac{\partial}{\partial u}\sum_i (f_{xi}u + f_{yi}v + f_t)^2 = 0 \qquad \sum (f_{xi}u + f_{yi}v + f_{ti}) f_{xi} = 0$$

$$\frac{\partial}{\partial v}\sum_i (f_{xi}u + f_{yi}v + f_t)^2 = 0 \qquad \sum (f_{xi}u + f_{yi}v + f_{ti}) f_{yi} = 0$$

Lucas & Kanade Method

$$\sum (f_{xi}u + f_{yi}v + f_{ti}) f_{xi} = 0$$

$$\sum (f_{xi}u + f_{yi}v + f_{ti}) f_{yi} = 0$$

$$\sum f_{xi}^2 u + \sum f_{xi} f_{yi} v = -\sum f_{xi} f_{ti}$$
$$\sum f_{xi} f_{yi} u + \sum f_{yi}^2 v = -\sum f_{yi} f_{ti}$$

$$\begin{bmatrix} \sum f_{xi}^2 & \sum f_{xi} f_{yi} \\ \sum f_{xi} f_{yi} & \sum f_{yi}^2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} -\sum f_{xi} f_{ti} \\ -\sum f_{yi} f_{ti} \end{bmatrix}$$

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Lucas & Kanade Method

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} \sum f_{xi}^2 & \sum f_{xi} f_{yi} \\ \sum f_{xi} f_{yi} & \sum f_{yi}^2 \end{bmatrix}^{-1} \begin{bmatrix} -\sum f_{xi} f_{ti} \\ -\sum f_{yi} f_{ti} \end{bmatrix}$$

$$\begin{bmatrix} u \\ v \end{bmatrix} = \frac{1}{\sum f_{xi}^2 \sum f_{yi}^2 - (\sum f_{xi} f_{yi})^2} \begin{bmatrix} \sum f_{yi}^2 & -\sum f_{xi} f_{yi} \\ -\sum f_{xi} f_{yi} & \sum f_{xi}^2 \end{bmatrix} \begin{bmatrix} -\sum f_{xi} f_{ti} \\ -\sum f_{yi} f_{ti} \end{bmatrix}$$

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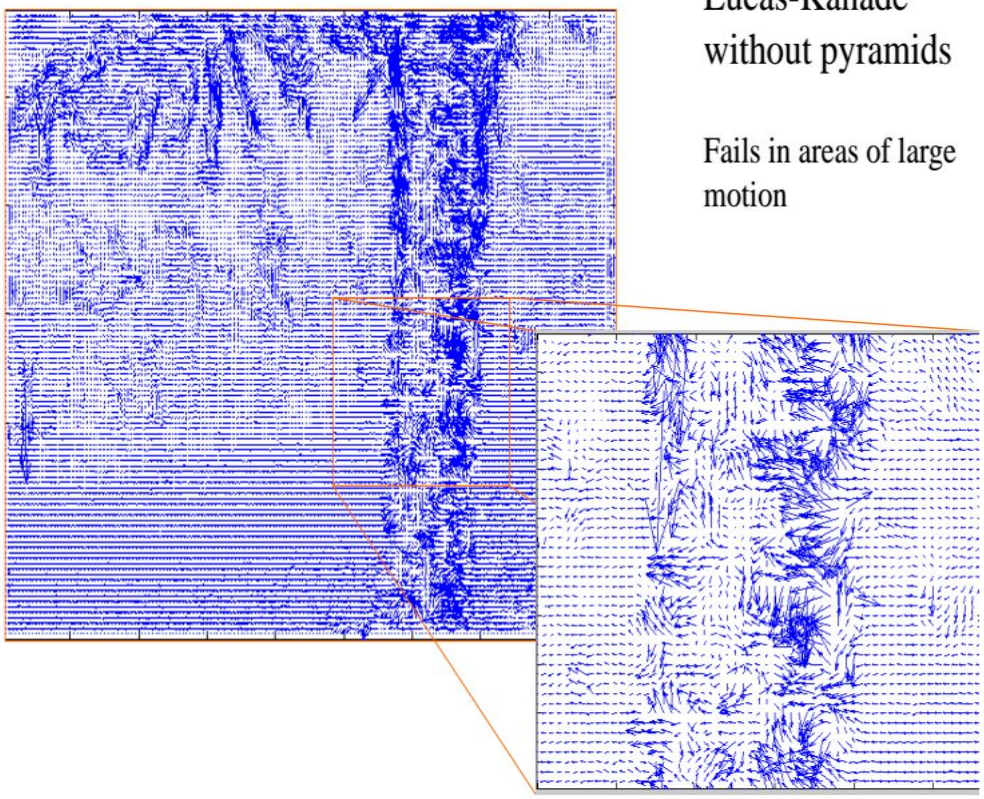
Lucas & Kanade Method

$$u = \frac{-\sum f_{yi}^2 \sum f_{xi} f_{ti} + \sum f_{xi} f_{yi} \sum f_{yi} f_{ti}}{\sum f_{xi}^2 \sum f_{yi}^2 - (\sum f_{xi} f_{yi})^2}$$

$$v = \frac{\sum f_{xi} f_{ti} \sum f_{xi} f_{yi} - \sum f_{xi}^2 \sum f_{yi} f_{ti}}{\sum f_{xi}^2 \sum f_{yi}^2 - (\sum f_{xi} f_{yi})^2}$$

Demo



Lucas-Kanade
without pyramids

Fails in areas of large
motion

Summary of optical flow

- Horn-Schunck and Lucas-Kanade optical methods work only for small motion.
- If object moves faster, the brightness changes rapidly,
  - then 2x2 or 3x3 masks fail to estimate spatiotemporal derivatives.
  - Optical flow vector are not aligned with each other
- Pyramids can be used to compute large optical flow vectors.

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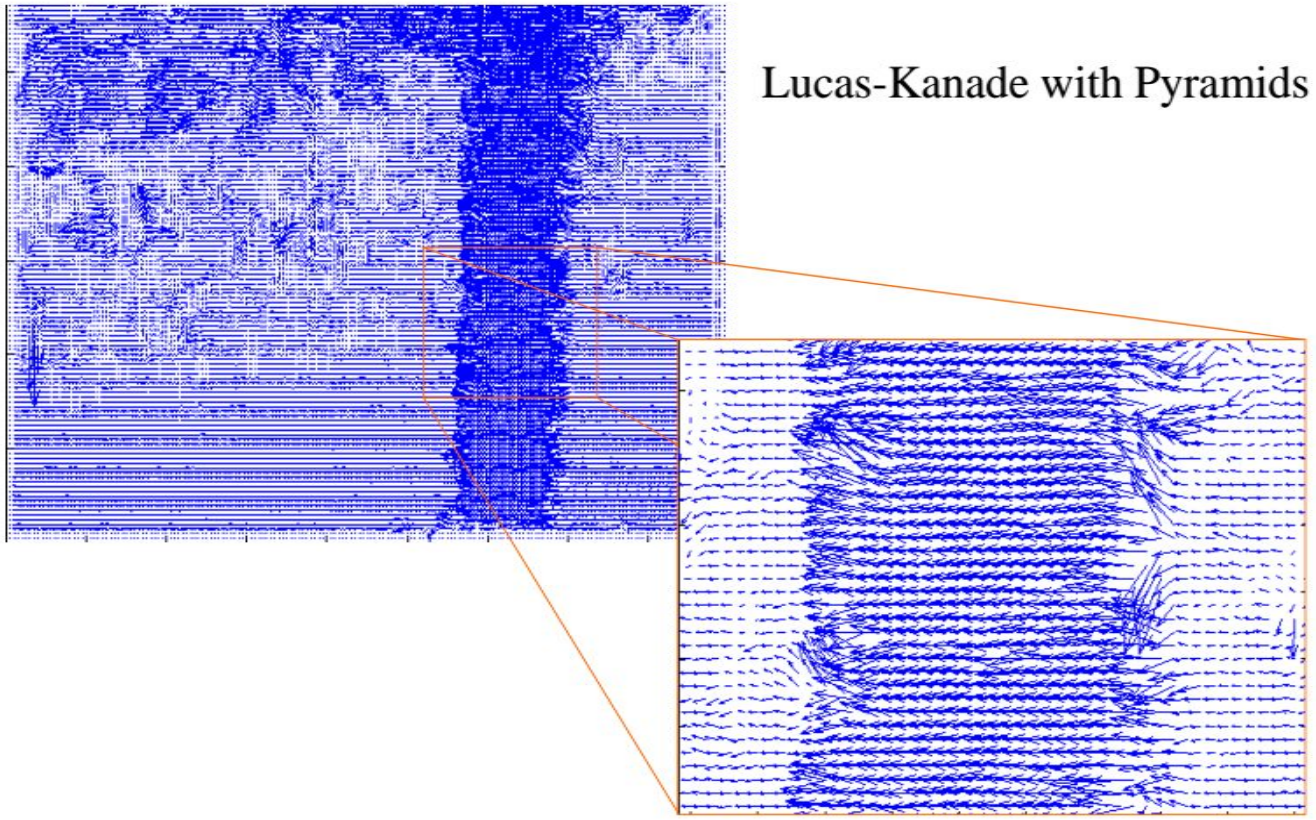
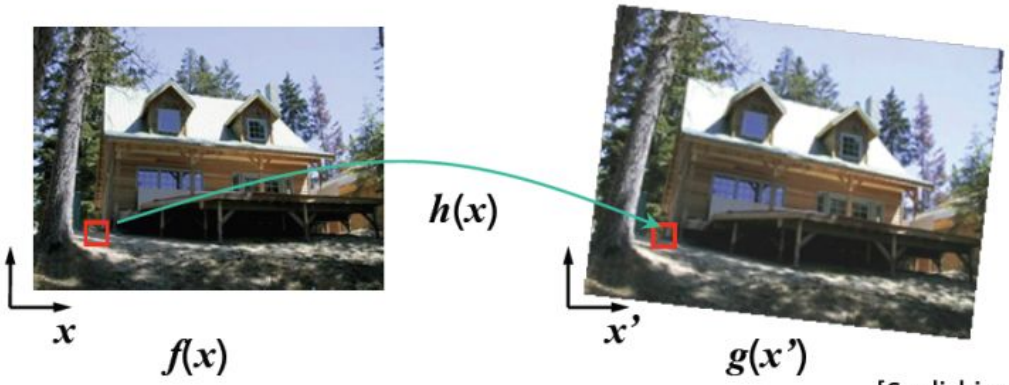
Demo



Applications of optical flow

Image registration

- we can use optical flow to register (i.e. align) images, by:
  - computing the flow with the entire image as a single region;
  - shifting the second image toward the first;
  - iterate until convergence.

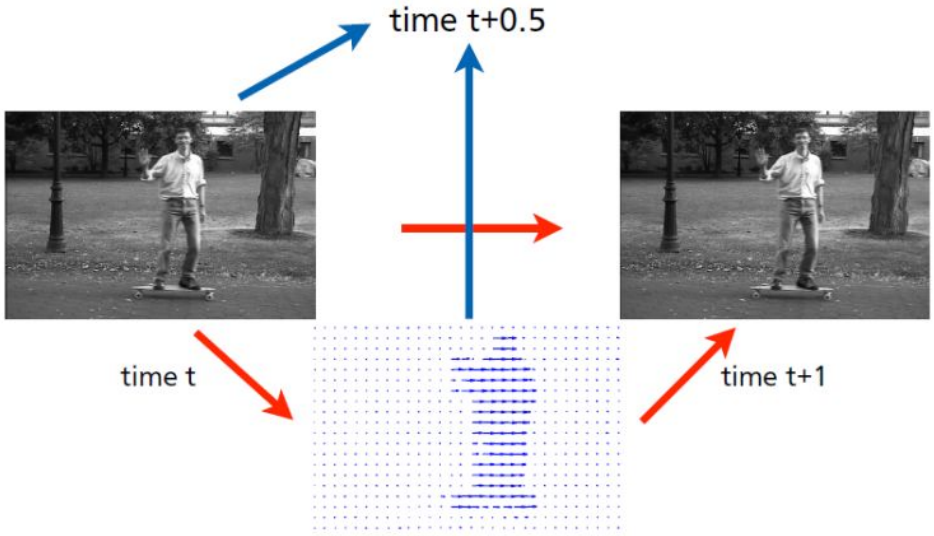


[Szeliski and Fleet]

Applications of optical flow

Video interpolation

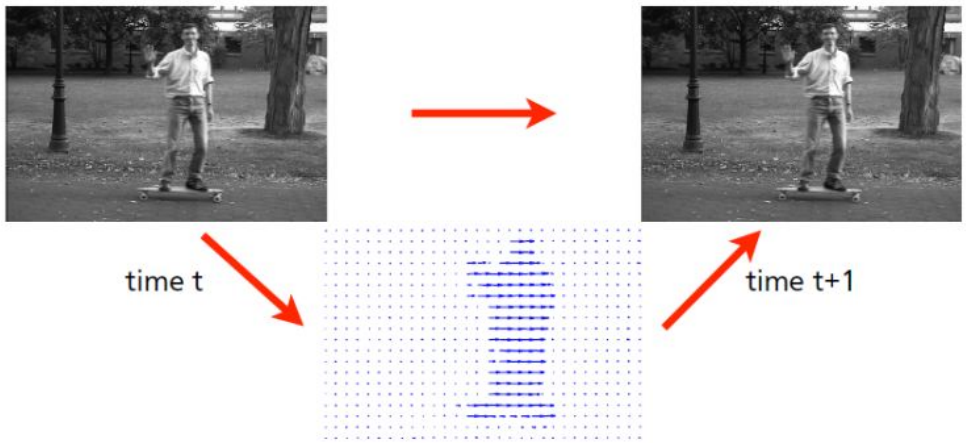
if we know the image motion, we can compute images at intermediate time steps: video interpolation



Applications of optical flow

Video compression

- if we wish to compress an image sequence, we can predict new frames using the flow, and only store how to “fix” this prediction
- the flow field is relatively easy to compress



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Tracking

- Tracking: following the position (and possibly its internal configuration) in time of an object of interest
- can be a single interesting point: **feature tracking**
- can be a target (e.g. airplane in airspace) -> **target tracking**
- can be a contour in 2D -> **active contouring**
- can be an object, intended as a region in an image sequence -> **object tracking**
- can be an articulated or deformable body in space -> pose estimation, motion capture

https://www.youtube.com/watch?v=RtwmKsQj9dM

Feature tracking

- feature tracking: track point features from frame to frame (most often used are corner features)
- finding matching image pixels p1 and p0 in frames I(t) and I(t + 1), corresponding to the same physical point
- features may appear and disappear, change with viewpoint

Simple KLT Algorithm

- Detect Harris corners in the first frame
- For each Harris corner compute motion (translation or affine) between consecutive frames.
- Link motion vectors in successive frames to get a track for each Harris point
- Introduce new Harris points by applying Harris detector at every n (10 or 15) frames
- Track new and old Harris points using steps 1-3

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Active contours for segmentation and tracking

- active contours is a catch-all name for methods that find the curve that best separates objects in an image
- This can also be called as segmentation
- But segmentation identifies all the pixel related to object
- Instead, we only track the shift in contour around the moving object
- can be edge-based or region based, i.e., based on separating regions with different statistics in some feature space

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Active contours demos

Demo on how active contours works:
https://www.youtube.com/watch?v=r610mi5hiHM

How to implement it in Matlab:
https://www.youtube.com/watch?v=v8-tyVXmUBo

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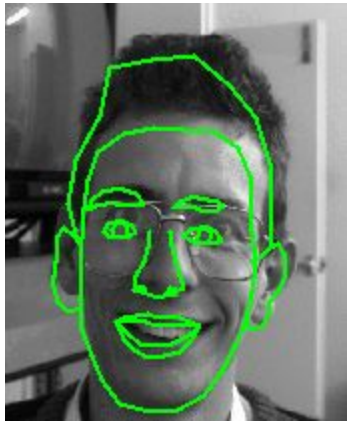
Active Shape Models

It provides an iterative method of matching a model to an image

Initial Pose



After 5 iterations

Convergence

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Active Shape Models

- building ASMs required labelling training images, with landmarks which represent correspondences
- every shape x is a cloud of points
- We identify the landmarks in current image and the next frame
- We create tracking vectors for each of the landmarks using tracking
- These tracking vectors can be used to define the shape model

Structure from motion

- Structure from Motion (SfM): technique utilizes a series of 2-dimensional images to reconstruct the 3-dimensional structure of a scene or object.
- SfM can produce point cloud based 3-D models similar to LiDAR.
  - given a video of an unknown scene captured by a moving camera whose motion is unknown
  - we want to reconstruct: camera motion and 3D scene geometry
- we assume that camera internal parameters are calibrated
- extrinsic parameters (translations and rotation between camera and world coordinates) are not know

Structure from motion

- interest points, typically corners, are tracked to allow for SfM
- why corners? the reason is that, as the geometry is not known, the search space is the entire image
- so, dense feature points would be very expensive to track
- corners are relatively sparse, well localised and cheap to compute
  - find the correspondence between corner points
  - then compute the fundamental matrix F from the correspondences
  - two image coordinates of the same 3D point must satisfy $x_1 \, F \, x_2 = 0$

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Structure from motion

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Structure from motion

A quick demo on how we implement SfM:

https://www.youtube.com/watch?v=i7ierVkXYa8

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Thanks!