Mechatronic Engineering program

Computer Vision
Video Processing

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Schedule

- Lecture 1: An Introduction
- Lecture 2: Image Segmentation
- Lecture 3: Image Features

- **Lecture 4: Video Processing**
  - Video Processing
  - Object Trackers
  - Optical Flow – Lukas-Kanade Algorithm

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Ideas

- Video contains generalized **motion** information

- Improved image processing method (e.g. gesture recognition)
- Object detection and **tracking**
- 3D structure of the world contained in motion (**scene reconstruction**)
- Continous image processing (e.g. scene monitoring methods)

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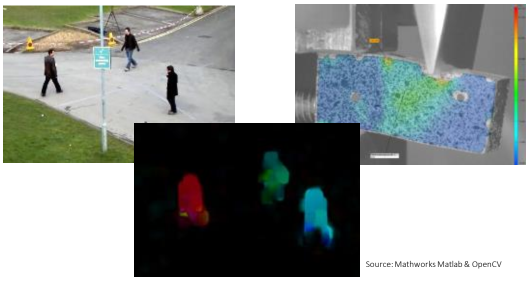
Ideas



Source: Mathworks Matlab & OpenCV

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Object tracking on binary images

- Very simple idea
- Detect objects on each frame (thresholding, labelling, regionprops)
- Find centroids of detected objects
- Join centroids of the same object by a continous trajectory

- Post processing – velocity and acceleration computation, trajectory shape analysis, approaches analysis…

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Object tracking on binary images

- An example (shown in Matlab)

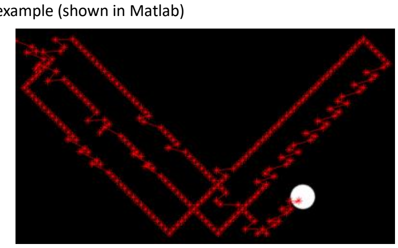

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Image correlation as object tracker

- Apply pattern matching for each frame of the sequence
- A pattern can be taken from the first frame of the sequence
- Or a pattern from frame (i-1) used to find the pattern on frame i

- Robust to change in intensity of a pattern
- Not robust to rotations and scaling of a pattern

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Image correlation as object tracker

- An example (shown in Matlab)

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Image correlation as object tracker

- An application for vibration analysis (shown im Matlab)

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Tracking using local features

- Review from the last time:

Local features describe the neighborhood of characteristic points – e.g. corners

We can build objects' representation out of these local features

- Local features can be tracked over the frames of video sequence
- Deformable object's motion can be tracked using this approach

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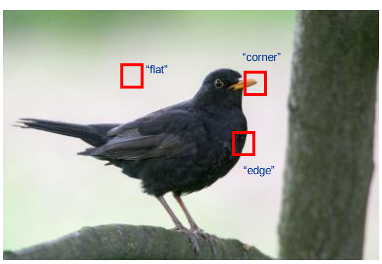
Corners in the image



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Recall Harris Corner Detector

The change of the image patch as we move by [dx dy]:

$$E(dx, dy) \approx [dx \quad dy] M \begin{bmatrix} dy \\ dy \end{bmatrix}$$

Matrix M is called **structural tensor**

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

The elements of the matrix are computed from **image gradient** (derivatives in x and y directions, e.g. obtained b Sobel masks) and w(x,y) is **Gaussian mask**

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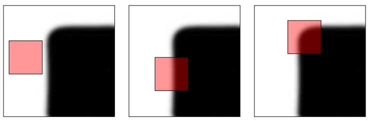
Harris Corner Detector

$$M = R \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R^T$$

The **eigenvalus** of M reveal the intensity change in two principal orthogonal gradient directions in the window



"flat" region: λ_1 and λ_2 are small, $\lambda_1 \sim \lambda_2$;

"edge": $\lambda_1 >> \lambda_2$ or $\lambda_2 >> \lambda_1$

"corner": λ_1 and λ_2 are large, $\lambda_1 \sim \lambda_2$;

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Harris Corner Detector

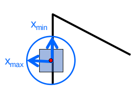
Why?

In general 2x2 matrix represents **a transformation** that changes **direction and scale** of a 2-element vector

There are 2 directions in space that are not rotated – **eigenvectors**

Scaling in these directions given by **eigenvalues**

Eigenvalues defines shifts with the smallest and largest change



$$Mx_{max} = \lambda_{max} x_{max}$$
$$Mx_{min} = \lambda_{min} x_{min}$$

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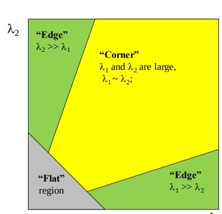
Harris Corner Detector

Harris gave us a simple **cornerness** score to assess both eigenvalues at the same time

$$R = \det(M) - \alpha \,\text{trace}(M)^2 = \lambda_1\lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$

α - an empirical constant (0.04 to 0.06)



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Local feature tracking challanges

The challanges of local feature tracking

- Figure out which features can be tracked the best
- Efficiently track across frames
- Some features may change appearance over time
- Drift: small errors accumulate over time
- Features may appear or disappear

- Two approaches – **sparse tracking** (a set of features) and **dense tracking** (in principle, all pixels, dense optical flow)

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Sparse tracking example

Detect „**good features to track"** (e.g. using Harris corner detector)

And track them

Example – using SURF features

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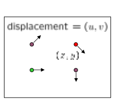
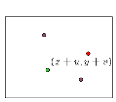
Optical Flow

Given two subsequent frames - estimate the feature translation



$I(x,y,t)$



$I(x,y,t+1)$

Lukas-Kanade method, basic assumptions

Brightness Constancy – feature do not change brightness over time

Small motion – only small displacements

Constancy of motions – neighbouring pixels move in the same way

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Optical Flow

Given two subsequent frames - estimate the feature translation
Apply **brightness constancy** equation

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

Small motion – we can use Taylor expansion at (x,y,t)

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

Substitute into brightness constancy equation

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

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Optical Flow

Optical flow equation for a single pixel

optical flow velocities

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

Image gradients
(at a given pixel)

temporal gradient

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Optical Flow

Compute all quantities in the equation $I_x u + I_y v + I_t = 0$

$$I_x = \frac{\partial I}{\partial x} \quad I_y = \frac{\partial I}{\partial y}$$

spatial derivative

High pass filter masks
Sobel Filter
Prewitt Filter
...

$$I_t = \frac{\partial I}{\partial t}$$

temporal derivative

Fame differencing
Subtracting consecutive frames

$$u = \frac{dx}{dt} \quad v = \frac{dy}{dt}$$

optical flow

Our unknowns to be found

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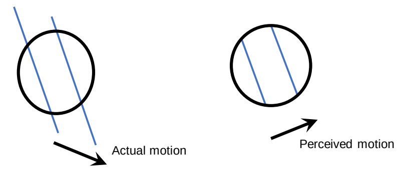
Optical Flow

In matrix form, we have $\nabla I \cdot [u \;\; v]^T + I_t = 0$

Problem: two unknowns (u,v) and one equation – we can find only the component perpendicular to the edge (**aperture problem**)



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Optical Flow

To solve this – apply **consistency of motion** of neighbouring pixels
N pixels in a small path move in the same way – we can build N equations
N=25 in the example (5x5 patch)

$$\begin{gathered} I_x(\boldsymbol{p}_1)u + I_y(\boldsymbol{p}_1)v = -I_t(\boldsymbol{p}_1) \\ I_x(\boldsymbol{p}_2)u + I_y(\boldsymbol{p}_2)v = -I_t(\boldsymbol{p}_2) \\ \vdots \\ I_x(\boldsymbol{p}_{25})u + I_y(\boldsymbol{p}_{25})v = -I_t(\boldsymbol{p}_{25}) \end{gathered}$$

Combine in a matrix form $\boldsymbol{A}\hat{\boldsymbol{x}} = \boldsymbol{b}$

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Optical Flow

Solution to the equation given in a form

$$A^\top A \hat{x} = A^\top b$$

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

$$A^\top A = \begin{bmatrix} \sum\limits_{p\in P} I_x I_x & \sum\limits_{p\in P} I_x I_y \\ \sum\limits_{p\in P} I_y I_x & \sum\limits_{p\in P} I_y I_y \end{bmatrix}$$

We have seen this before, its the same matrix as in Harris Corner Detector

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Optical Flow

What should be propertiees of this matrix?

$$A^\top A = \begin{bmatrix} \sum_{p \in P} I_x I_x & \sum_{p \in P} I_x I_y \\ \sum_{p \in P} I_y I_x & \sum_{p \in P} I_y I_y \end{bmatrix}$$

- Invertible
- Should not be „small", both **eigenvalues** should not be small
- Well-conditioned, one eigenvalues **should not be** much larger than the second one

- Exactly the same properties as for **corner detection**

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Lukas-Kanade approach - problems

The smoothness of flow field **is not** preserved

Good for tracking rigid body mostly translation – cars, planes, objects in the scene etc.
Not good for tracking motion that is smooth – deofrmable bodies etc., rotations, scaling etc.

Solution: impose flow smoothness on your solution
A class of variational methos – e.g. **Horn-Schunck optical flow**

For every pixel we want: $\min_{\boldsymbol{u},\boldsymbol{v}} \sum_{i,j} \left\{ E_s(i,j) + \lambda E_d(i,j) \right\}$

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Horn-Schunck optical flow

For every pixel we want

$$\min_{\boldsymbol{u},\boldsymbol{v}} \sum_{i,j} \left\{ E_s(i,j) + \lambda E_d(i,j) \right\}$$

Smoothness Constraint (Flow gradients)

Brightness constancy assumption

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

Optimized using variational calculus methods
Give dense and smooth flow fields

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Optical Flow examples

Examples in Matlab

Horn Schunck OF

Lukas Kanade OF

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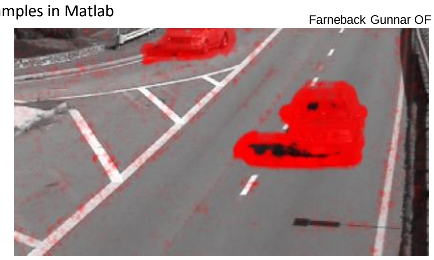
Optical Flow examples

Examples in Matlab

Farneback Gunnar OF



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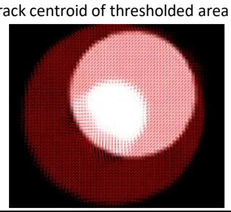
Optical flow for tracking rigid objects

- Compute dense flow velocity vectors for each pixel in each frame
- Threshold the flow velocity rejecting all pixels with small velocity magnitude
- Compute and track centroid of thresholded area



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Thank you for your attention

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