



Autonomous Mobile Robots

Module 19: Feature extraction based on visual
appearance



Feature extraction based on visual appearance

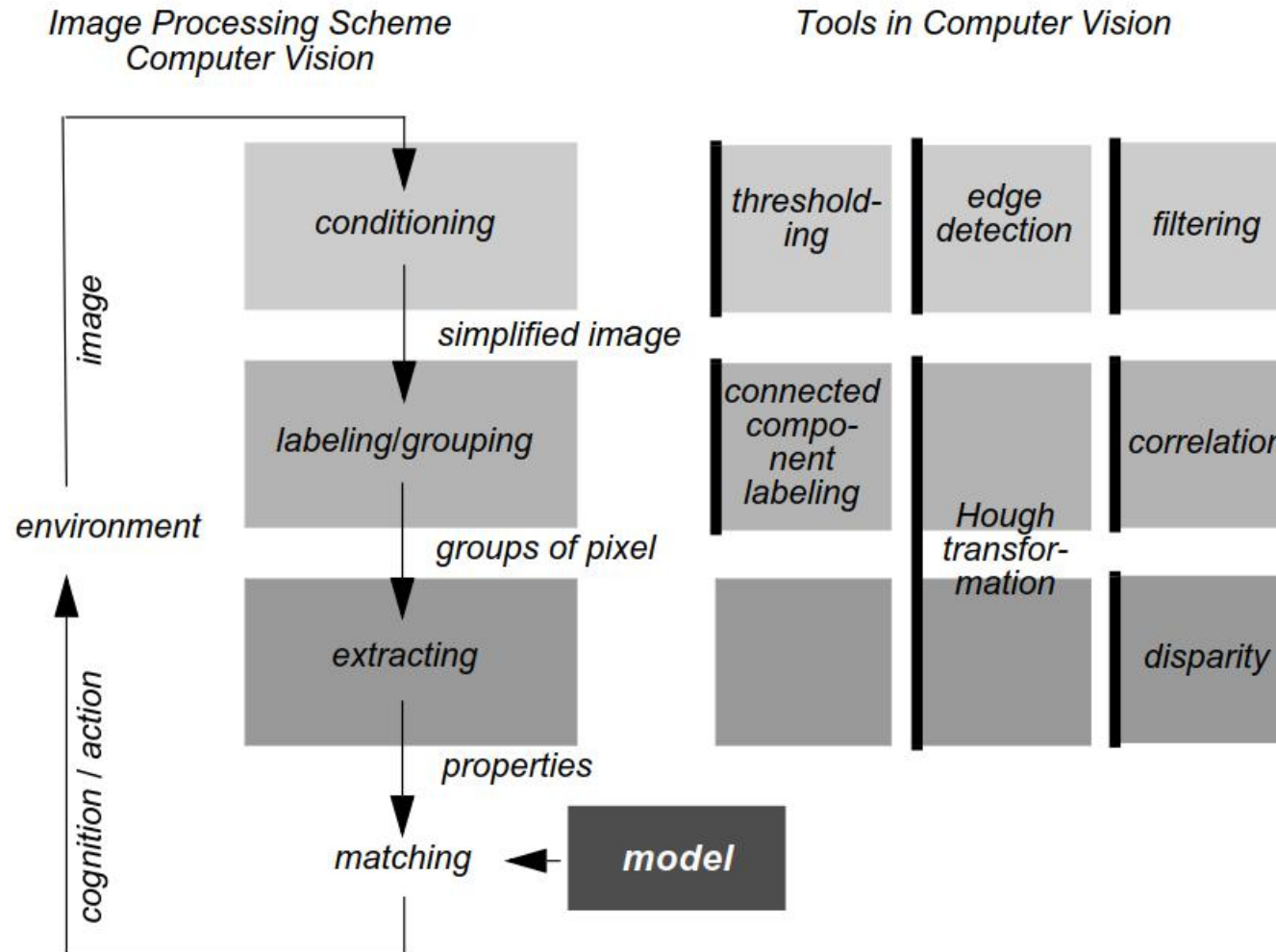
- Appearance-based feature extraction relevant to mobile robotics
- The method must operate in real-time
- Method must be robust to real-world conditions outside laboratory
- Cannot make a lot of assumptions on the illumination and color
- Vision-based interpretation tries to reduce the information as much as possible
- A sonar sensor can produce data at around 50 bits per second, a camera can output 240 million bits per second - hence large volume of data is to be dealt with
- Hence vision-based feature extraction is essential to reduce volume



Feature extraction based on visual appearance

- This large volume of information needs to be reduced to a smaller size by keeping most important things and discarding relatively less important things
- Vision-based feature extraction can be classified into two types
 - **Spatially localized features** – features found in regions of image, at specific locations
 - **Whole-image features** – functions of entire image or large area of image
- All vision sensors provide images with noise, need a filtering or preprocessing step to reduce noise


Feature extraction based on visual appearance



Feature extraction based on visual appearance

- **Image Preprocessing**

- Before extracting features, image needs to be smoothed
- If feature extraction is done without this step, there will be a lot of noisy results and misleading features
- To smooth the images, a standard process adopted is to perform convolution with Gaussian distribution function



Smooth → low pass filter : removes high frequency .

Feature extraction based on visual appearance

Smoothing : Convolution with Gaussian dist. fn.

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t-\tau) d\tau$$

For images: $I' = G \otimes I$

I : original image

G : Gaussian : discrete kernel.

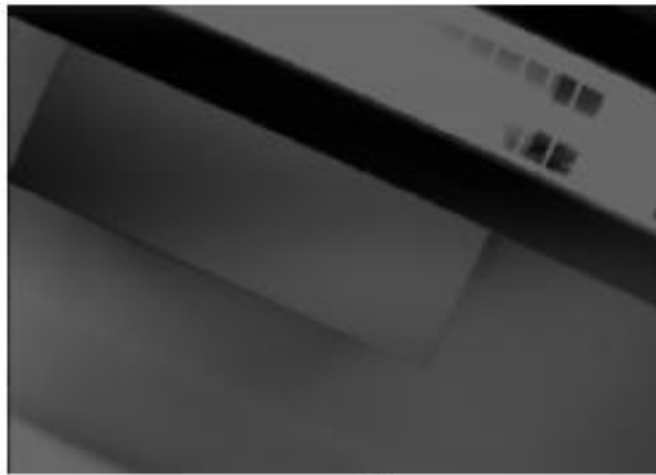
Eg: 3x3 · $G = \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$

This operation is essentially a weighted averaging.
low pass filter

5	7	21	11	.	18	29
9	11	14	13	.	71	33
3	8	5	14	.	.	.
.
.
.
19	15	75	.	.	51	33
61	49	87	.	.	36	43

Feature extraction based on visual appearance

- We will focus only on spatially localized features
- Within spatially localized features, we will focus only on edge detection
- Edge detection is a very commonly used local feature extractor

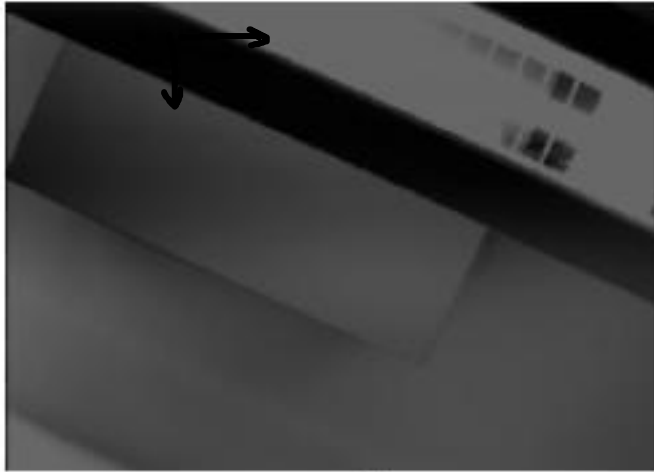


a)

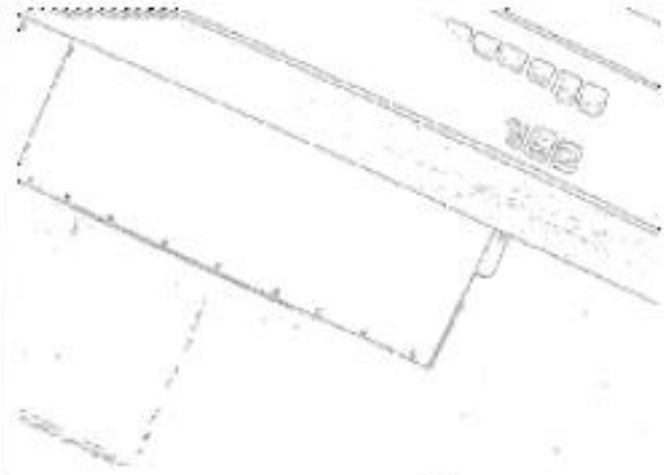


b)

Feature extraction based on visual appearance



a)



b)

Differentiating $\text{const} = 0$

$$\frac{\partial}{\partial x} \quad \frac{\partial}{\partial y}$$

$$\frac{\partial}{\partial t}$$

Threshold T · edge pixel
needs to exceed

- We can understand edge detection as a differentiation process, or a gradient operation
- Edges define regions in the image plane where significant change in image brightness takes place
- The edge image has significantly lesser volume of information than original image

Feature extraction based on visual appearance

- Since edge is a sharp transition, it is important that the image is smoothed first before performing edge detection
- Canny edge detection is one example of edge detection algorithm

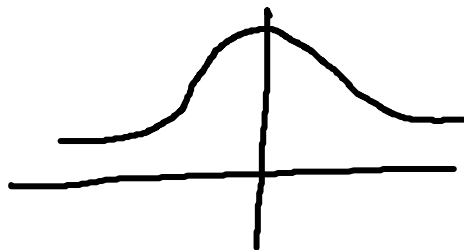
John Canny 1983

Gaussian smoothing $I_1 = G \otimes I$

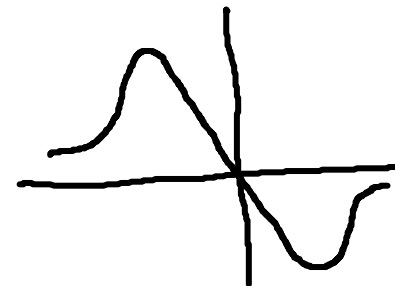
Derivative of smoothed image $I_2 = f \otimes I_1 = (I_1)' = (G \otimes I)'$

Can represent with single convolution operation

$$I' = G' \otimes I$$

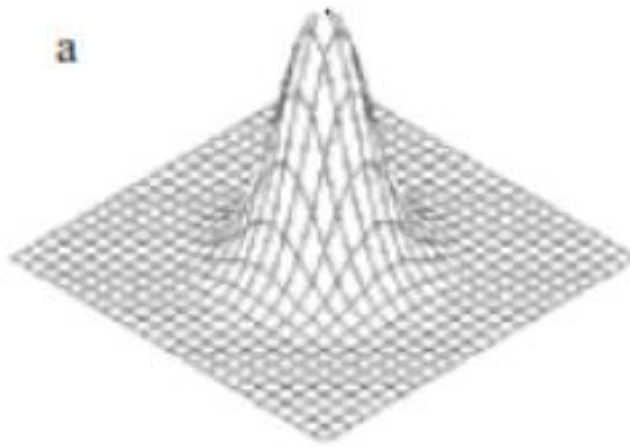


$$\frac{1}{\sqrt{2\pi}\sigma} e^{-x^2/2\sigma^2}$$

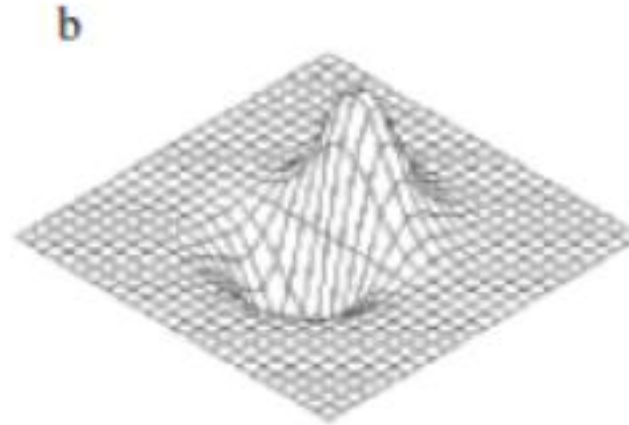


$$\frac{-x}{\sqrt{2\pi}\sigma^3} e^{-x^2/2\sigma^2}$$

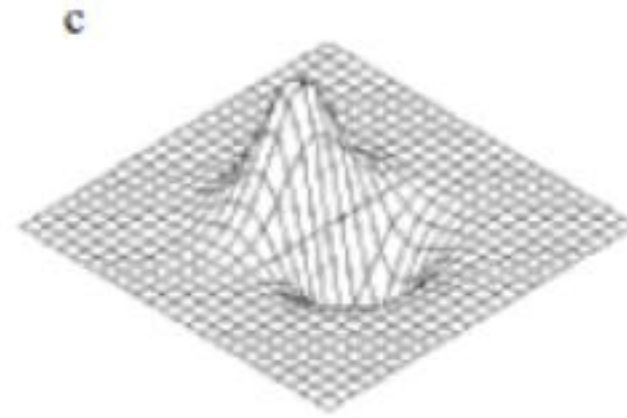
Feature extraction based on visual appearance



$$G(x)G(y)$$



$$G'(x)G(y)$$



$$G'(y)G(x)$$

$$f_v(x, y) = G'(x)G(y)$$

$$f_h(x, y) = G'(y)G(x)$$

$$R_v = f_v \otimes I$$

$$R_h = f_h \otimes I$$

Other features:
- Floor plane

$$R(x, y) = \sqrt{R_v^2 + R_h^2}$$

IF $R(x, y) > T$ (threshold)
then mark as an edge.



SASTRA
ENGINEERING · MANAGEMENT · LAW · SCIENCES · HUMANITIES · EDUCATION
DEEMED TO BE UNIVERSITY
(U/S 3 of the UGC Act, 1956)



THINK MERIT | THINK TRANSPARENCY | THINK SASTRA

Autonomous Mobile Robots
MCT 308

Autonomous Mobile Robots

Module 20: Unit III - Localization & Mapping
Introduction



Unit-III

LOCALIZATION AND MAPPING: Introduction - Bayes filter – Kalman Filter - Extended Kalman Filter - Information Filter - Histogram Filter - Particle Filter – Challenges of Localization- Map Representation- Probabilistic Map based Localization-Monte carlo localization- Landmark based navigation-Globally unique localization- Positioning beacon systems- Route based localization – Mapping - Metrical maps - Grid maps - Sector maps – Hybrid Maps – SLAM.

SLAM - Simultaneous Localization and Mapping

- Navigation : to go from one place to another autonomously
- Has 4 building blocks
- Perception: interpret sensor data
- Localization: determine position in environment
- Cognition: decide how to act to achieve goals
- Motion Control: modulate motor output

Recursive State Estimation

State: Collection of all aspects of a robot and its environment that can impact the future course of the robot

- State can change over time: dynamic state - position, velocity of moving robot, car
- State can be static - position of wall in a room
- Typical states we will deal with:
 - Mobile robot pose: position and orientation
 - For planar robot: pose is given by x, y, Ψ
 - Drone robot pose: (x, y, z) : 3 positions, (Φ, Θ, Ψ) : 3 orientations
 - Locations and features of surrounding objects in environment
 - Locations and velocities of moving objects and people
- State variable is represented by x



Environment Interaction

- Robot can influence the state of its environment through its actuators - **Control actions**
- Robot can gather information about the state through its sensors - **Sensor measurements**
- In practice, a robot continuously executes control action and measurements concurrently
- Control actions are represented by u
- Sensor measurements are represented by z
- Sensing measurements provide information about environment's state, hence it increases robot's knowledge
- Motion leads to a loss of knowledge due to uncertainty in actuation