Sensor Modalities

- Sensor modality:
  - *Sensors which measure same form of energy and process it in similar ways*
  - *"Modality" refers to the raw input used by the sensors*

- Different modalities:
  - *Sound*
  - *Pressure*
  - *Temperature*
  - *Light*
    - *Visible light*
    - *Infrared light*
    - *X-rays*
    - *Etc.*

Classification of Sensors

- What:
  - *Proprioceptive sensors*
    - *measure values internally to the system (robot),*
    - *e.g. motor speed, wheel load, heading of the robot, battery status*
  - *Exteroceptive sensors*
    - *information from the robots environment*
    - *distances to objects, intensity of the ambient light, unique features.*
- How:
  - *Passive sensors*
    - *energy coming for the environment*
  - *Active sensors*
    - *emit their proper energy and measure the reaction*
    - *better performance, but some influence on environment*

General Classification (1)

General classification (typical use)	Sensor Sensor System	PC or EC	A or P
Tactile sensors (detection of physical contact or closeness; security switches)	Contact switches, bumpers	EC	P
	Optical barriers	EC	A
	Noncontact proximity sensors	EC	A
Wheel/motor sensors (wheel/motor speed and position)	Brush encoders	PC	P
	Potentiometers	PC	P
	Synchros, resolvers	PC	A
	Optical encoders	PC	A
	Magnetic encoders	PC	A
	Inductive encoders	PC	A
	Capacitive encoders	PC	A
Heading sensors (orientation of the robot in relation to a fixed reference frame)	Compass	EC	P
	Gyroscopes	PC	P
	Inclinometers	EC	A/P

A, active; P, passive; P/A, passive/active; PC, proprioceptive; EC, exteroceptive.

General Classification (2)

General classification (typical use)	Sensor Sensor System	PC or EC	A or P
Ground-based beacons (localization in a fixed reference frame)	GPS Active optical or RF beacons Active ultrasonic beacons Reflective beacons	EC EC EC EC	A A A A
Active ranging (reflectivity, time-of-flight, and geometric triangulation)	Reflectivity sensors Ultrasonic sensor Laser rangefinder Optical triangulation (1D) Structured light (2D)	EC EC EC EC EC	A A A A A
Motion/speed sensors (speed relative to fixed or moving objects)	Doppler radar Doppler sound	EC EC	A A
Vision-based sensors (visual ranging, whole-image analysis, segmentation, object recognition)	CCD/CMOS camera(s) Visual ranging packages Object tracking packages	EC	P

Characterizing Sensor Performance

- Basic sensor response ratings
  - *Range*
    - *lower and upper limits*
  - *Resolution*
    - *minimum difference between two values*
  - *Linearity*
    - *variation of output signal as function of the input signal*
  - *Bandwidth or Frequency*
    - *the speed with which a sensor can provide a stream of readings*
    - *usually there is an upper limit depending on the sensor and the sampling rate*
    - *lower limit is also possible, e.g. acceleration sensor*
    - *one also has to consider signal delay*

In Situ Sensor Performance (1)

Characteristics that are especially relevant for real world environments

- Sensitivity
  - *ratio of output change to input change*
  - *however, in real world environment, the sensor has very often high sensitivity to other environmental changes, e.g. illumination*
- Cross-sensitivity
  - *sensitivity to environmental parameters that are orthogonal to the target parameters*
  - *influence of other active sensors*
- Error / Accuracy
  - *difference between the sensor's output and the true value*

error

$$\left(accuracy = 1 - \frac{|m - v|}{v}\right)$$

***m* = measured value**

***v* = true value**

In Situ Sensor Performance (2)

Characteristics that are especially relevant for real world environments

- Systematic error -> deterministic errors
  - *caused by factors that can (in theory) be modeled -> prediction*
  - *e.g. calibration of a laser sensor or of the distortion cause by the optic of a camera*
- Random error -> non-deterministic
  - *no prediction possible*
  - *however, they can be described probabilistically*
  - *e.g. Hue instability of camera, black level noise of camera …*
- Precision
  - reproducibility *of sensor results*

Characterizing Error: The Challenges in Mobile Robotics

- Mobile Robot has to perceive, analyze and interpret the state of the surrounding
- Measurements in real world environment are dynamically changing and error prone.
- Examples:
  - *changing illuminations*
  - *specular reflections*
  - *light or sound absorbing surfaces*
  - *cross-sensitivity of robot sensor to robot pose and robot-environment dynamics*
    - *rarely possible to model -> appear as random errors*
    - *systematic errors and random errors might be well defined in controlled environment.* This is not the case for mobile robots !!

Multi-Modal Error Distributions: The Challenges in …

- Behavior of sensors modeled by probability distribution (random errors)
  - *usually very little knowledge about the causes of random errors*
  - *often probability distribution is assumed to be symmetric or even Gaussian*
  - *however, it is important to realize how wrong this can be!*
  - *Examples:*
    - *Sonar (ultrasonic) sensor might overestimate the distance in real environment and is therefore not symmetric*

      Thus the sonar sensor might be best modeled by two modes:
      - mode for the case that the signal returns directly
      - mode for the case that the signals returns after multi-path reflections.
    - *Stereo vision system might correlate to images incorrectly, thus causing results that make no sense at all*

Proximity Sensors

- Measure relative distance (range) between sensor and objects in environment

- Most proximity sensors are active

- Common Types:
  - *Sonar (ultrasonics)*
  - *Infrared (IR)*
  - *Bump and feeler sensors*

Range Sensors (time of flight) (1)

- Large range distance measurement -> called range sensors
- Range information:
  - *key element for localization and environment modeling*
- Ultrasonic sensors as well as laser range sensors make use of propagation speed of sound or electromagnetic waves respectively. The traveled distance of a sound or electromagnetic wave is given by

$$d = c \cdot t$$

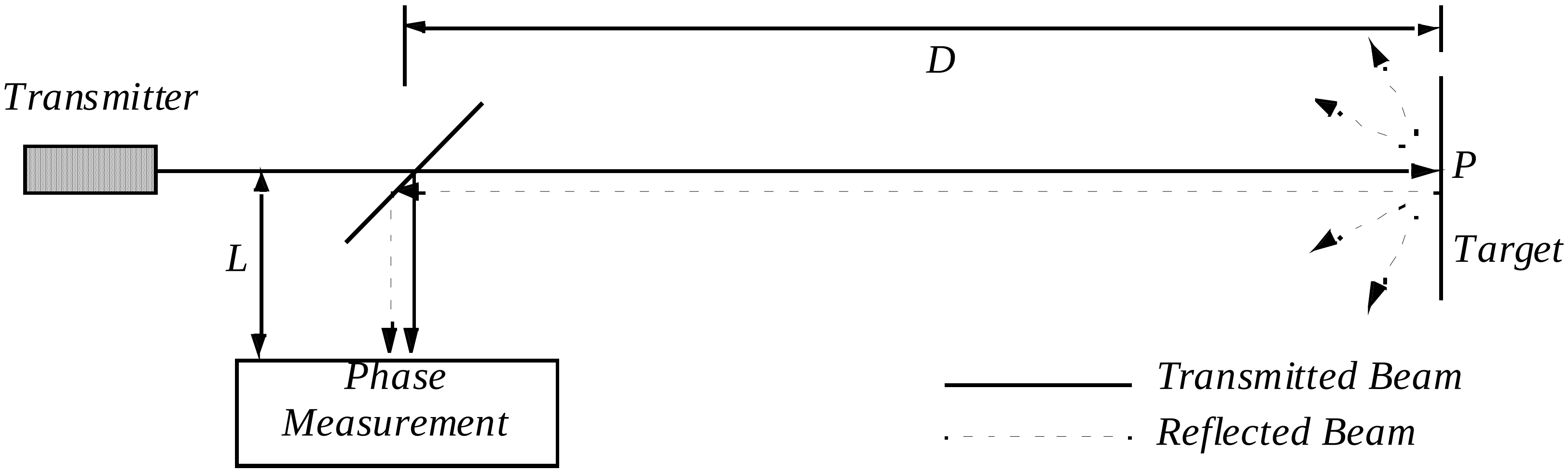
- Where
  - *d = distance traveled (usually round-trip)*
  - *c = speed of wave propagation*
  - *t = time of flight.*

Range Sensors (time of flight) (2)

- It is important to point out
  - *Propagation speed v of sound: 0.3 m/ms*
  - *Propagation speed v of of electromagnetic signals: 0.3 m/ns,*
    - *one million times faster.*
  - *3 meters*
    - *is 10 ms ultrasonic system*
    - *only 10 ns for a laser range sensor*
    - *time of flight t with electromagnetic signals is not an easy task*
    - *laser range sensors expensive and delicate*

- The quality of time of flight range sensors manly depends on:
  - *Uncertainties about the exact time of arrival of the reflected signal*
  - *Inaccuracies in the time of fight measure (laser range sensors)*
  - *Opening angle of transmitted beam (ultrasonic range sensors)*
  - *Interaction with the target (surface, specular reflections)*
  - *Variation of propagation speed*
  - *Speed of mobile robot and target (if not at stand still)*

Laser Range Sensor (time of flight, electromagnetic)



- Transmitted and received beams coaxial
- Transmitter illuminates a target with a collimated beam
- Received detects the time needed for round-trip
- A mechanical mechanism with a mirror sweeps
  - *2 or 3D measurement*

Laser Range Sensor (time of flight, electromagnetic)

- Confidence in the range is inversely proportional to the square of the received signal amplitude.

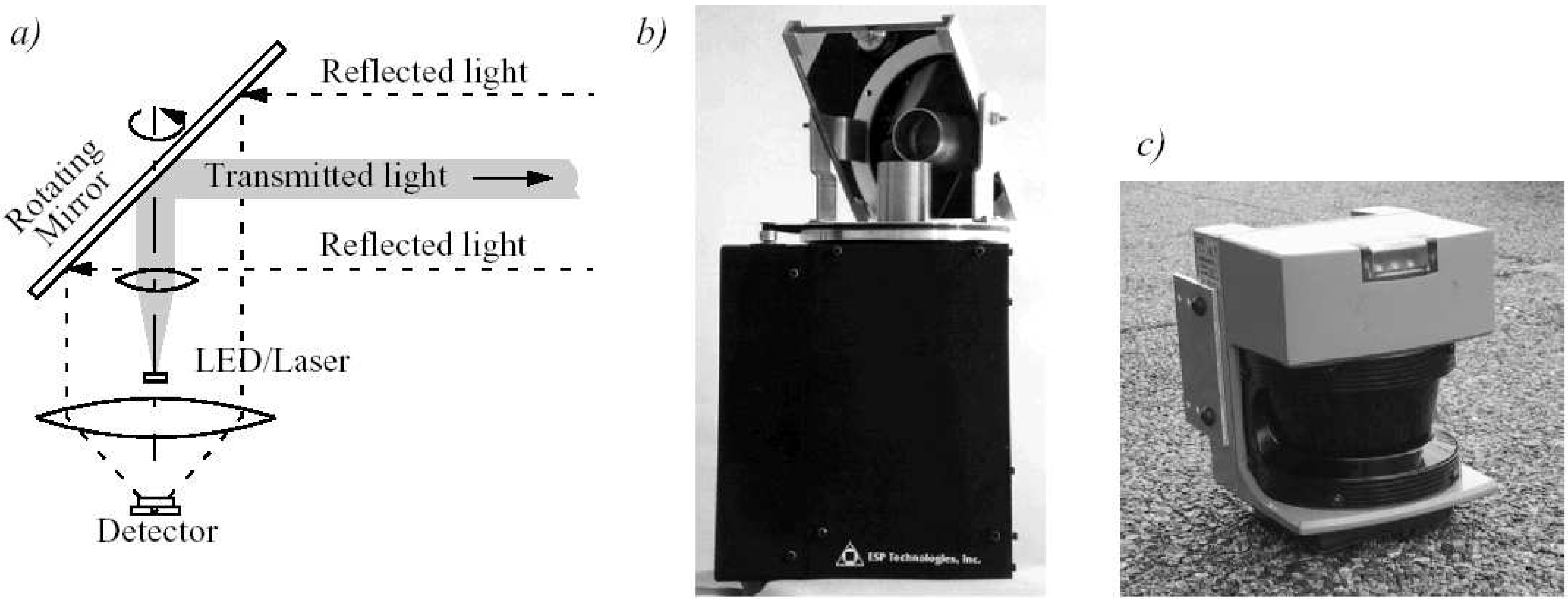
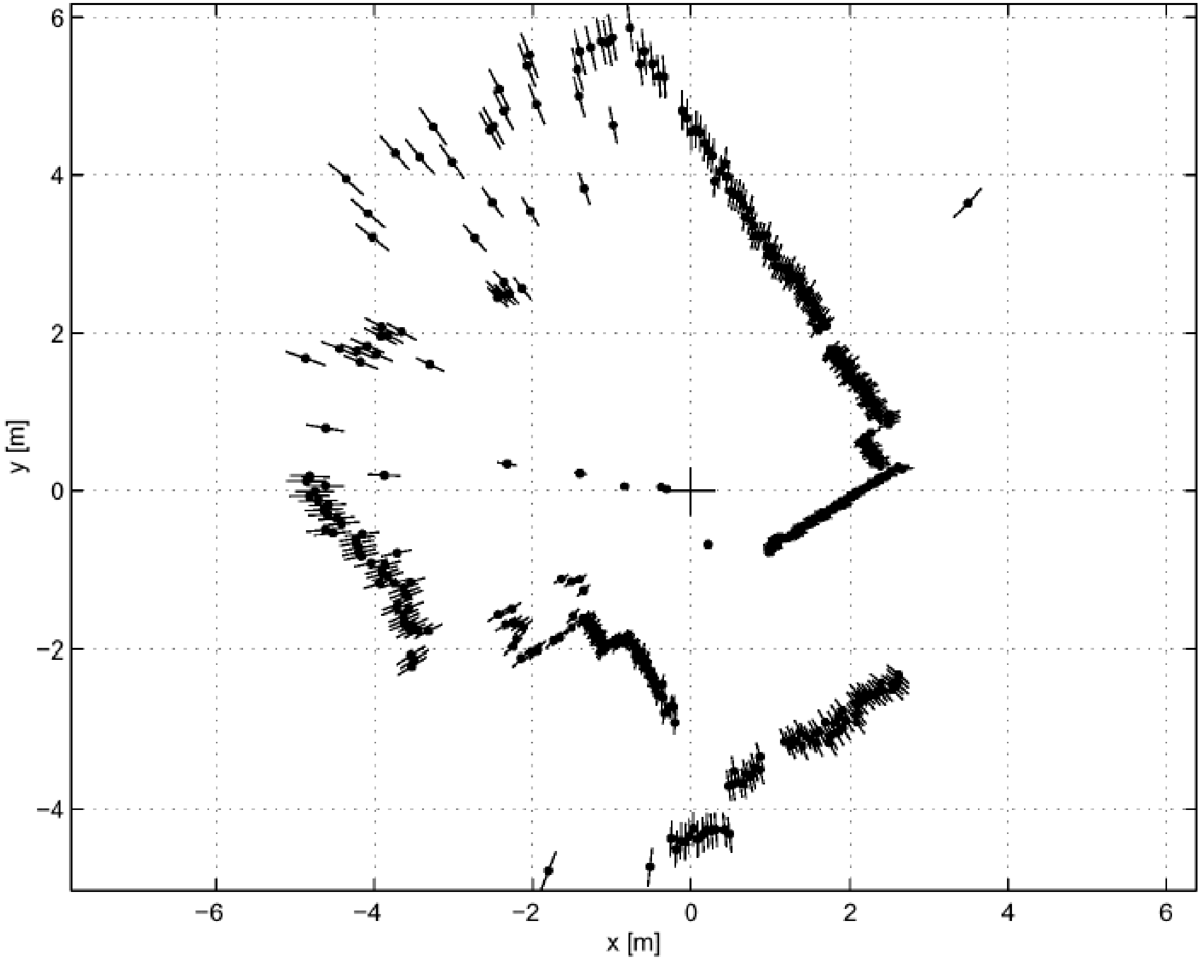


Figure 4.11
(a) Schematic drawing of laser range sensor with rotating mirror; (b) Scanning range sensor from EPS Technologies Inc.; (c) Industrial 180 degree laser range sensor from Sick Inc., Germany

Laser Range Sensor (time of flight, electromagnetic)

- Typical range image of a 2D laser range sensor with a rotating mirror. The length of the lines through the measurement points indicate the uncertainties.



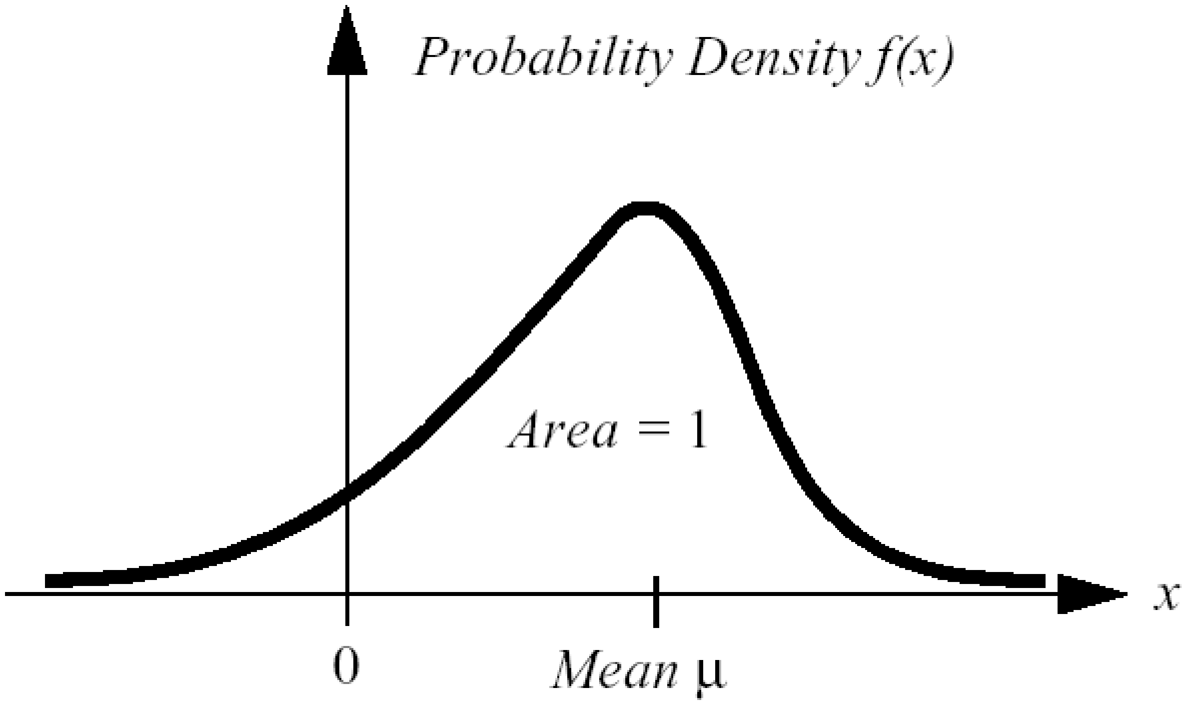
Uncertainty Representation

- Sensing is always related to uncertainties.
  - *What are the sources of uncertainties?*
  - *How can uncertainty be represented or quantified?*
  - *How do they propagate - uncertainty of a function of uncertain values?*
  - *How do uncertainties combine if different sensor reading are fused?*
  - *What is the merit of all this for mobile robotics?*
- Some definitions:
  - *Sensitivity:* *G=out/in*
  - *Resolution:* *Smallest change which can be detected*
  - *Dynamic Range:* $value_{max}$ / resolution (10^4 - 10^6)
  - *Accuracy:* $error_{max}$ = (measured value) - (true value)
- Errors are usually unknown:

deterministic ⟷ *non deterministic (random)*

Uncertainty Representation

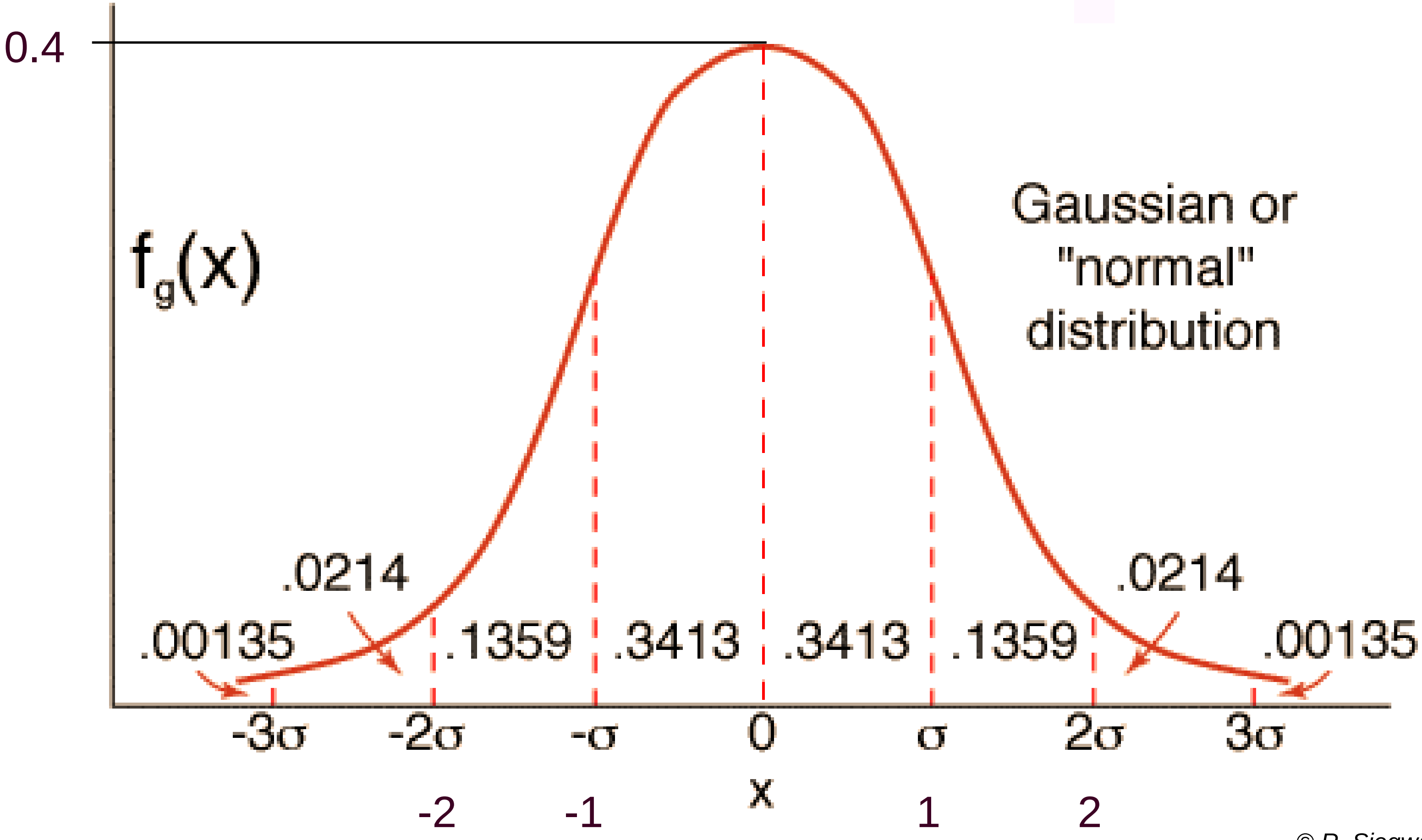
- Statistical representation and independence of random variables



Gaussian Distribution

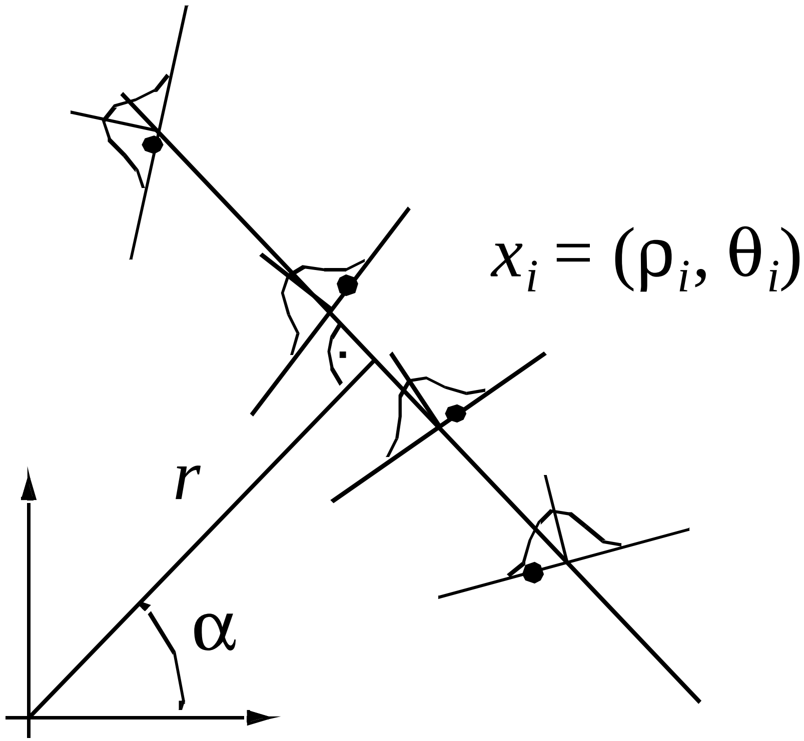
$\mu = 0$ and $\sigma = 1$

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$



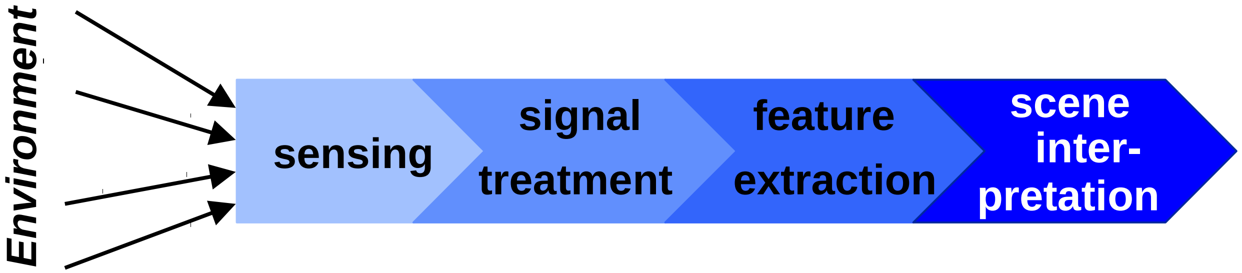
The Error Propagation Law: Motivation

- Imagine extracting a line based on point measurements with uncertainties.
- The model parameters ρ_i (length of the perpendicular) and θ_i (its angle to the abscissa) describe a line uniquely.



- The question:
  - ➢ *What is the uncertainty of the extracted line knowing the uncertainties of the measurement points that contribute to it ?*

Feature Extraction - Scene Interpretation



- A mobile robot must be able to determine its relationship to the environment by sensing and interpreting the measured signals.
  - *A wide variety of sensing technologies are available as we have seen in previous section.*
  - *However, the main difficulty lies in interpreting these data, that is, in deciding what the sensor signals tell us about the environment.*

  - *Choice of sensors (e.g. indoor, outdoor, walls, free space …)*
  - *Choice of the environment model*

Features

- Features are distinctive elements or geometric primitives of the environment.

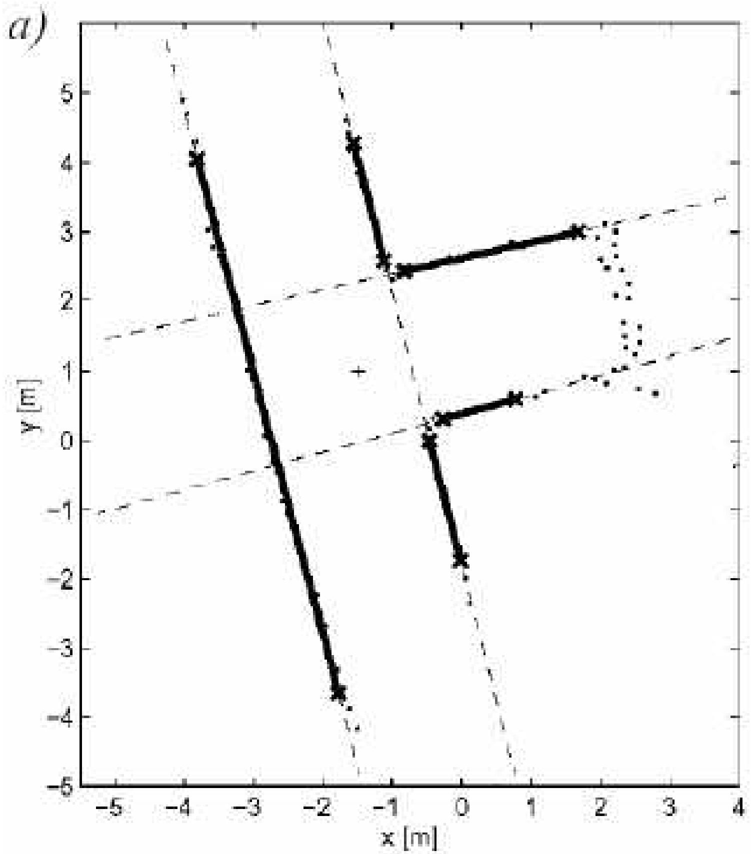
- They usually can be extracted from measurements and mathematically described.
  - *low-level features (geometric primitives) like lines, circles*
  - *high-level features like edges, doors, tables or trash cans.*

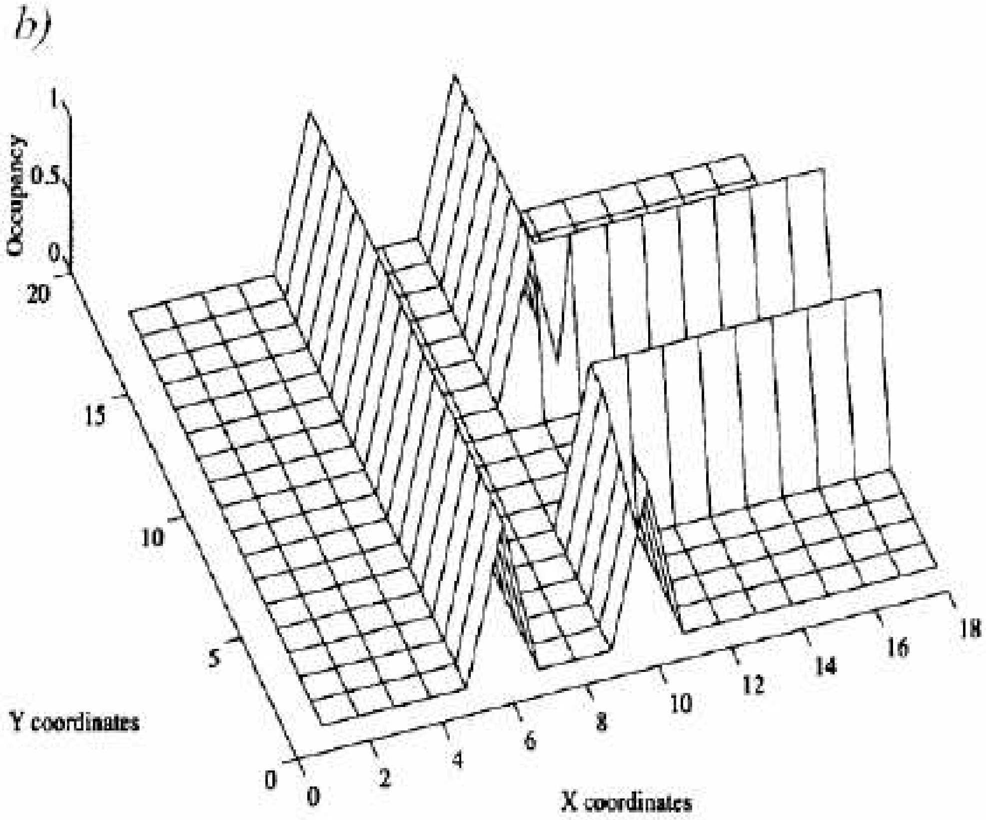
In mobile robotics features help for localization and map building.

Environment Representation and Modeling → Features

- Environment Representation
  - *Continuous Metric* → x, y, θ
  - *Discrete Metric* → *metric grid*
  - *Discrete Topological* → *topological grid*
- Environment Modeling
  - *Raw sensor data, e.g. laser range data, grayscale images*
    - *large volume of data, low distinctiveness*
    - *makes use of all acquired information*
  - *Low level features, e.g. line other geometric features*
    - *medium volume of data, average distinctiveness*
    - *filters out the useful information, still ambiguities*
  - *High level features, e.g. doors, a car, the Eiffel tower*
    - *low volume of data, high distinctiveness*
    - *filters out the useful information, few/no ambiguities, not enough information*

Environment Models: Examples





A: Feature based Model

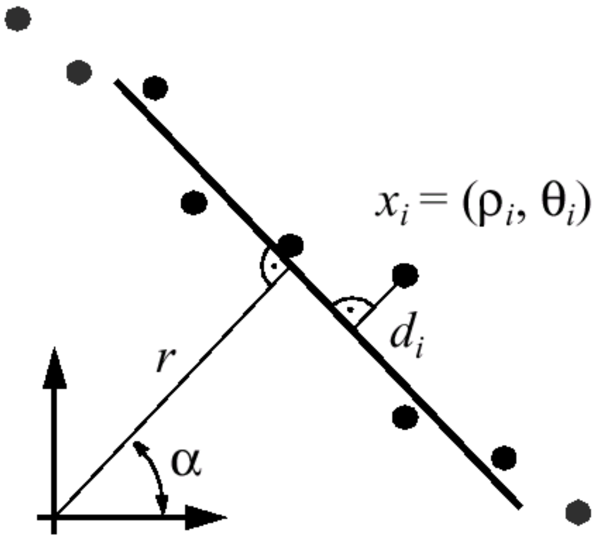
B: Occupancy Grid

Feature extraction based on range images

- Geometric primitives like line segments, circles, corners, edges
- For most other geometric primitives, the parametric description of the features becomes too complex, and no closed form solutions exist.
- However, lines segments are very often sufficient to model the environment, especially for indoor applications.

Features Based on Range Data: Line Extraction (1)

$$\rho_i \cos(\theta_i - \alpha) - r = d_i$$



- Least Squares

$$S = \sum_i d_i^2 = \sum_i (\rho_i \cos(\theta_i - \alpha) - r)^2$$

$$\frac{\partial S}{\partial \alpha} = 0 \qquad \frac{\partial S}{\partial r} = 0$$

- Weighted Least Squares

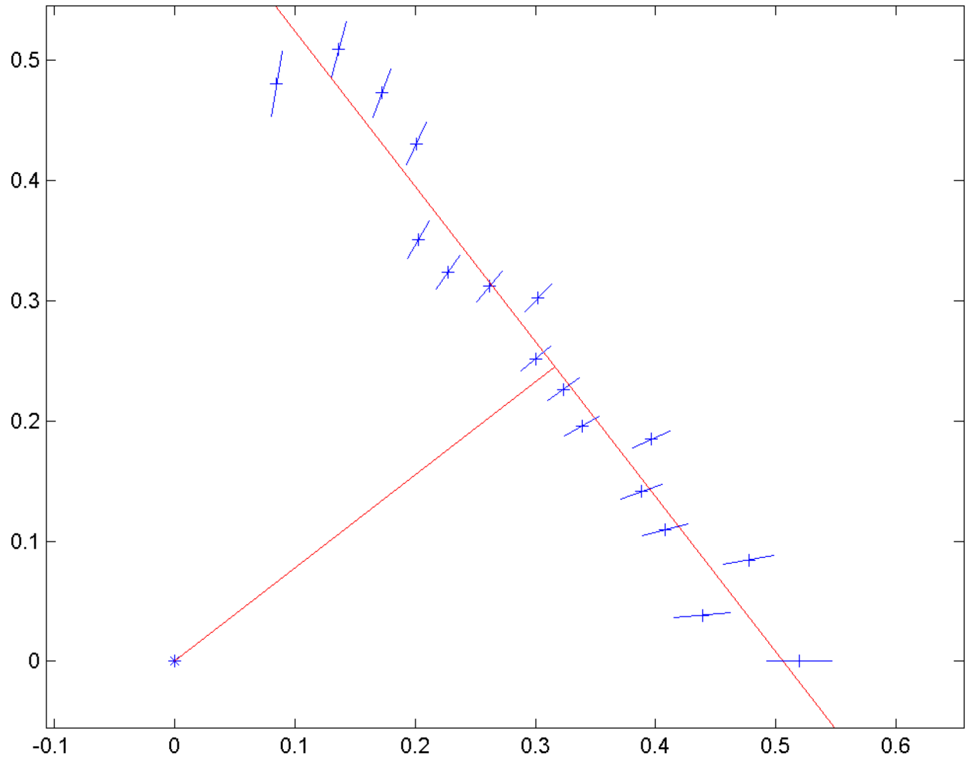
$$w_i = 1/\sigma_i^2$$

$$S = \sum w_i d_i^2 = \sum w_i (\rho_i \cos(\theta_i - \alpha) - r)^2$$

Features Based on Range Data: Line Extraction (2)

- 17 measurements
- error (σ) proportional to ρ^2
- weighted least squares:

$$w_i = 1/\sigma_i^2$$

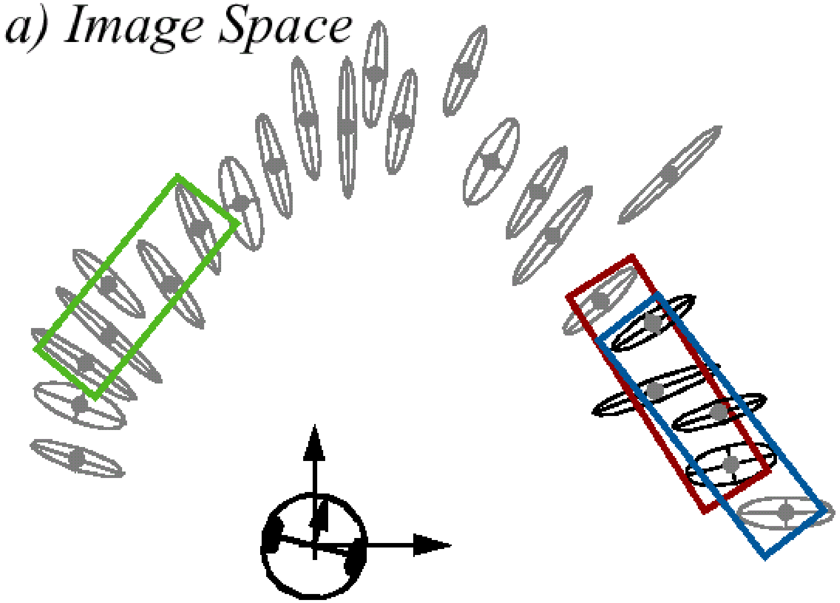


$$\alpha = \frac{1}{2}\operatorname{atan}\left(\frac{\sum w_i\rho_i^2\sin 2\theta_i - \frac{2}{\sum w_i}\sum\sum w_i w_j \rho_i \rho_j \cos\theta_i \sin\theta_j}{\sum w_i\rho_i^2\cos 2\theta_i - \frac{1}{\sum w_i}\sum\sum w_i w_j \rho_i \rho_j \cos(\theta_i + \theta_j)}\right)$$

$$r = \frac{\sum w_i \rho_i \cos(\theta_i - \alpha)}{\sum w_i}$$

Segmentation for Line Extraction

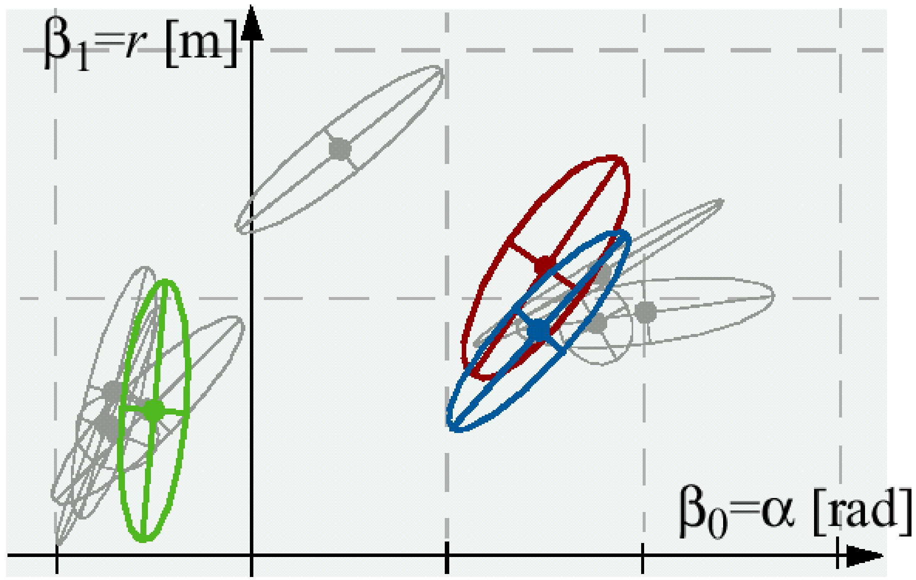
a) Image Space



A set of n_f neighboring points of the image space

$$(x_j - \bar{x})^T (x_j - \bar{x}) \leq d_m$$

b) Model Space



Evidence accumulation *in the model space*
→ Clusters of normally distributed vectors

Fig 4.36 Clustering: Finding neighboring segments of a common line