Hochschule
Bonn-Rhein-Sieg
University of Applied Sciences

Bonn-Aachen
International Center for
Information Technology

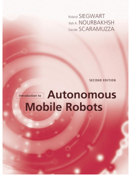
Institute for AI and
Autonomous Systems

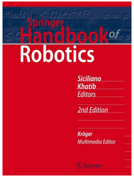
Perception

Sensors and Sensor Models

Dr. Alex Mitrevski
Master of Autonomous Systems

Structure

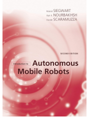


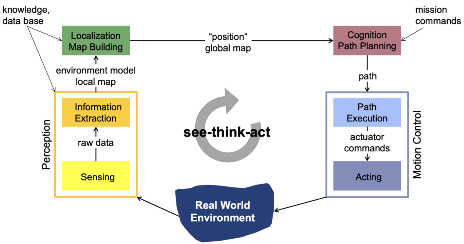


- Perception overview
- Sensors
- Sensor models

Perception Overview

Perception: An Integral Part of a Robot's Operation





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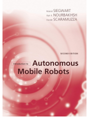

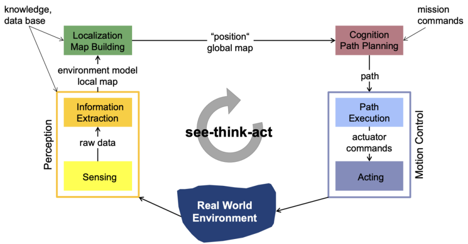

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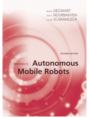

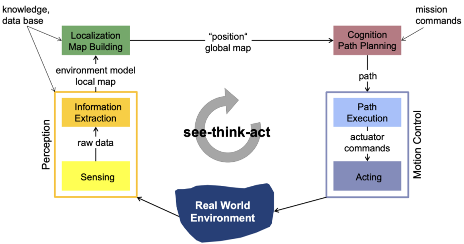

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- Perception encompasses the use of information from any sensory modality, as well as from multimodal data

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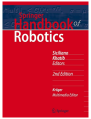
- Perception is essential for maintaining the robot's belief because it can be used to verify whether the observations correspond to the model
  - As we will see later in the course, this is the main idea behind SLAM algorithms

Prototypical Perception Process



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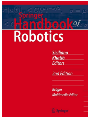

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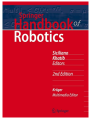

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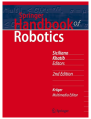

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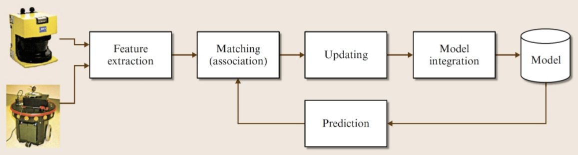

Sensors

Classification of Sensors

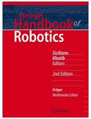

Table 5.1 Classification of sensors frequently used in robotics according to sensing objective (proprioception (PC)/exteroception (EC)) and method (active/passive)

Classification	Sensor type	Sens	A/P
Tactile sensors	Switches/bumpers	EC	P
	Optical barriers	EC	A
	Proximity	EC	P/A
Haptic sensors	Contact arrays	EC	P
	Force/torque	PC/EC	P
	Resistive	EC	P
Motor/axis sensors	Brush encoders	PC	P
	Potentiometers	PC	P
	Resolvers	PC	A
	Optical encoders	PC	A
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Heading sensors	Compass	EC	P
	Gyroscopes	PC	P
	Inclinometers	EC	A/P
Beacon based	GPS	EC	A
(postion wrt	Active optical	EC	A
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	Reflective beacons	EC	A
Ranging	Capacitive sensor	EC	P
	Magnetic sensors	EC	P/A
	Camera	EC	P/A
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	Laser range	EC	A
	Structured light	EC	A
Speed/motion	Doppler radar	EC	A
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	Camera	EC	P
	Accelerometer	EC	P
Identification	Camera	EC	P
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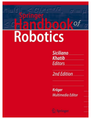

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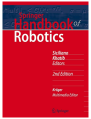

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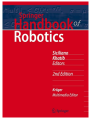

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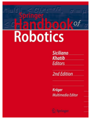

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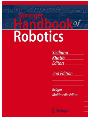

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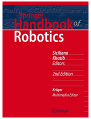

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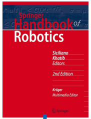
   - **Active sensors trigger the process of data collection and measure the received signal**

Encoders



- An encoder is a **device that measures the speed and often the direction of rotational motion**, typically using active sensing

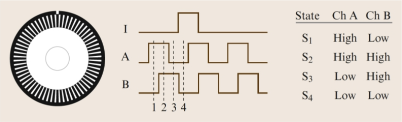
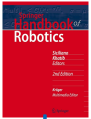


Fig. 5.5 Sketch of the quadrature encoder disc, and output from photodetectors placed over each of the two pattern. The corresponding state changes are shown on the *right*

Encoders



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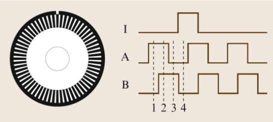
- An encoder measures a signal of high / low patterns of windows on a rotating disk



State	Ch A	Ch B
S_1	High	Low
S_2	High	High
S_3	Low	High
S_4	Low	Low

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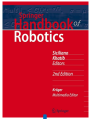


- An encoder is a **device that measures the speed and often the direction of rotational motion**, typically using active sensing
- An encoder measures a signal of high / low patterns of windows on a rotating disk
- To measure the direction of motion, a **quadrature encoder** can be used, where **two concentric disks are placed with a phase offset**; two signals are thus measured here (as shown on the left)

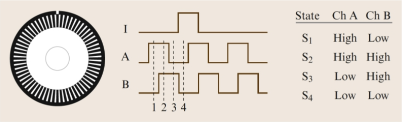
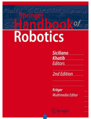
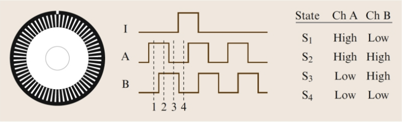


Fig. 5.5 Sketch of the quadrature encoder disc, and output from photodetectors placed over each of the two pattern. The corresponding state changes are shown on the *right*

Encoders



- An encoder is a **device that measures the speed and often the direction of rotational motion**, typically using active sensing
- An encoder measures a signal of high / low patterns of windows on a rotating disk
- To measure the direction of motion, a **quadrature encoder** can be used, where **two concentric disks are placed with a phase offset**; two signals are thus measured here (as shown on the left)
- **Optical encoders**, which are more precise, are very common on commercial robots
  - An encoders is used for every wheel / manipulator joint



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Accelerometers

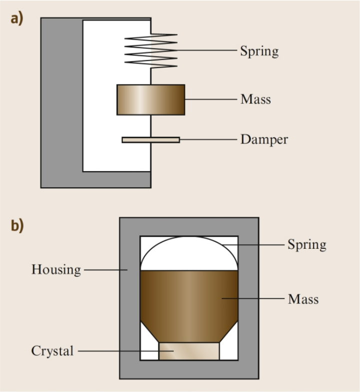
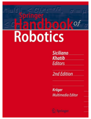
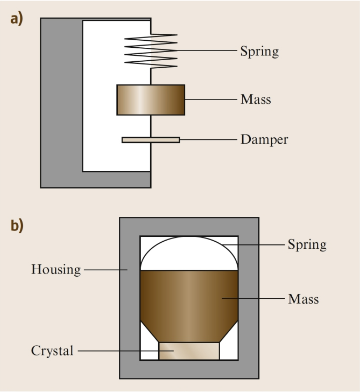


Fig. 29.6 Accelerometers. **(a)** Mechanical accelerometer; **(b)** piezoelectric accelerometer ◄

- An accelerometer **measures external forces** that are applied to it (along three separate axes)

Accelerometers





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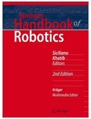

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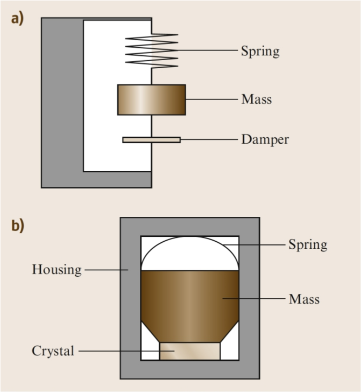
$$F_{ext} = m\ddot{x} + \gamma\dot{x} + kx$$



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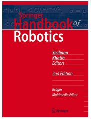

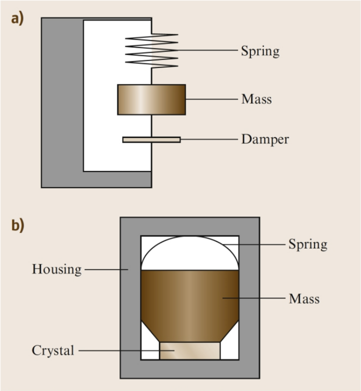

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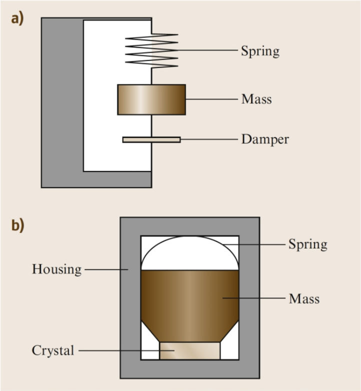
Accelerometers



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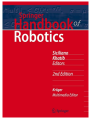

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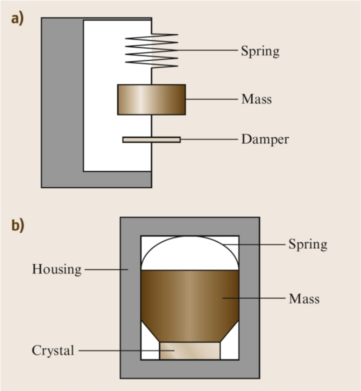
Accelerometers



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- Force / torque sensors operate based on similar principles

Gyroscopes

- A gyroscope is used to **measure rotational velocity**

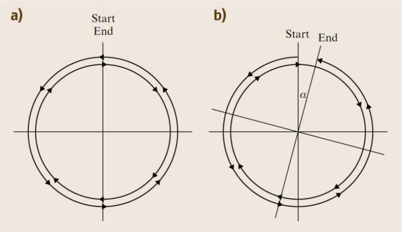
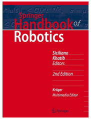


Fig.29.4a,b Circular light path. **(a)** Stationary path; **(b)** Moving path

Gyroscopes



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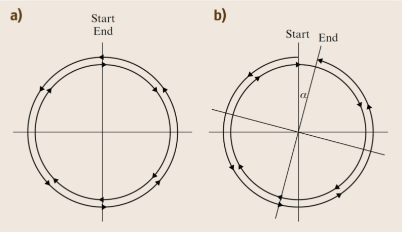

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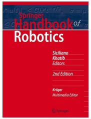

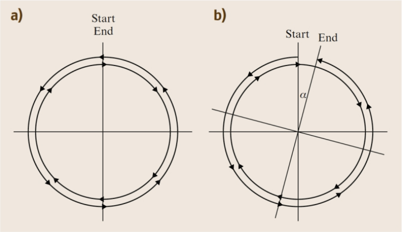

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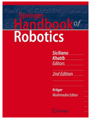
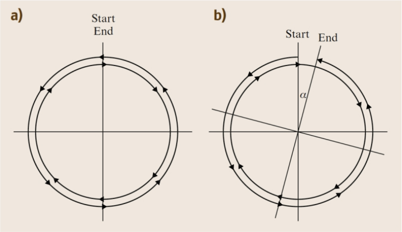
Gyroscopes





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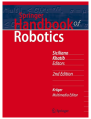
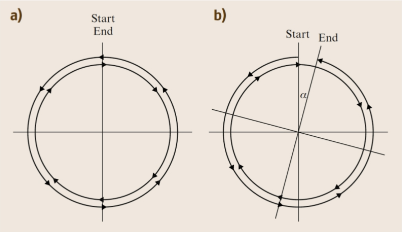
Gyroscopes





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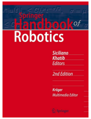
  - **MEMS gyroscopes**: Measure the Coriolis force experienced by an object travelling in a straight line a rotating frame

Inertial Measurement Units (IMUs)



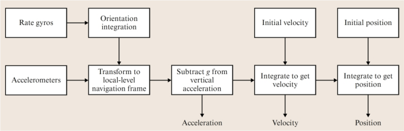
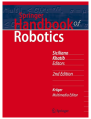
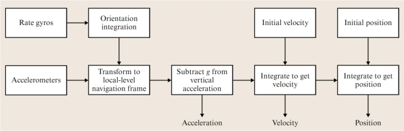


Fig. 29.7 IMU block diagram

- An IMU **combines an accelerometer and a gyroscope to measure both linear acceleration and rotational velocity**

Inertial Measurement Units (IMUs)





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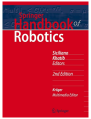

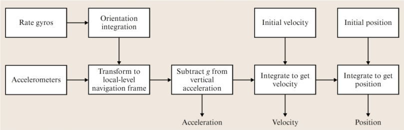

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- The overall operation of an IMU is illustrated in the diagram on the left
- As errors in the gyroscope and accelerometer measurements accumulate, **IMU measurements tend to drift**; an external reference is thus often required for error correction

Global Positioning System (GPS)

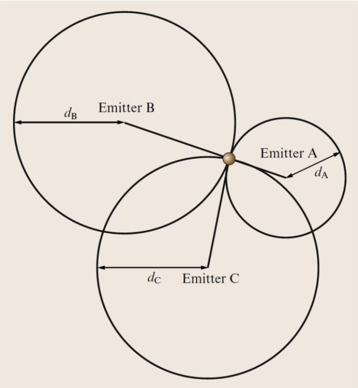
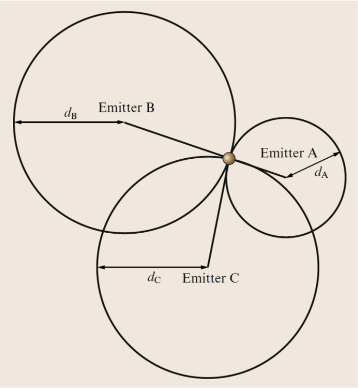


Fig. 29.8 GPS trilateration on the plane

- GPS is a **positioning system based on a collection of satellites orbiting around Earth**, which continuously emit data packages as radio signals

Global Positioning System (GPS)



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- **Based on known positions of the satellites** (monitored by ground stations) and **on time differences in signal propagation from the satellites to the receiver**, a position estimate for the receiver can be computed

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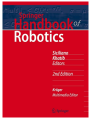

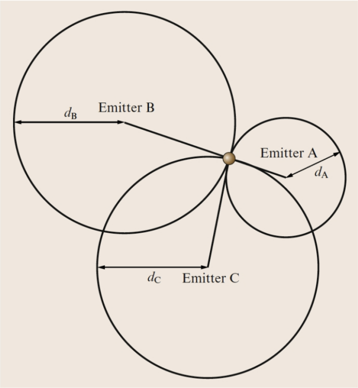

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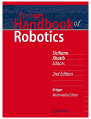
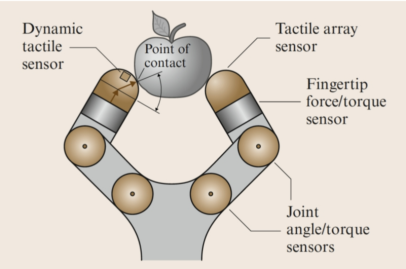
- GPS-based position estimates are computed using **multilateration** (an example with three measurements is shown on the left)

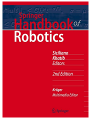
Tactile Sensors

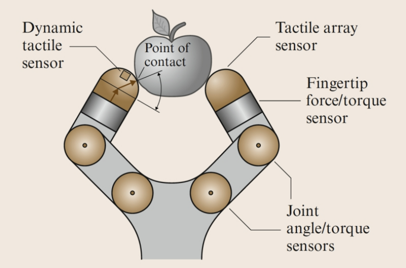


- Tactile sensors **measure deformations of a material** and are used to induce a robot with a touch sense



Tactile Sensors





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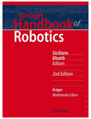
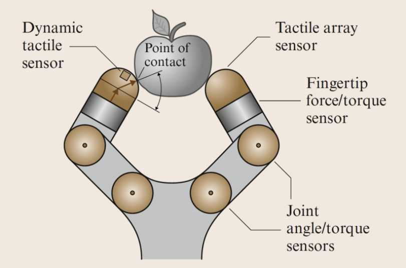
- These are often designed as tactile pressure sensing arrays, which can operate based on different principles:

Tactile Sensors





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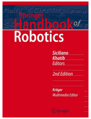

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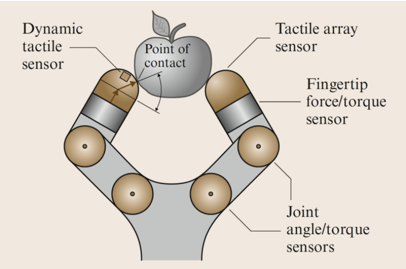

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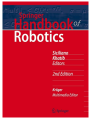

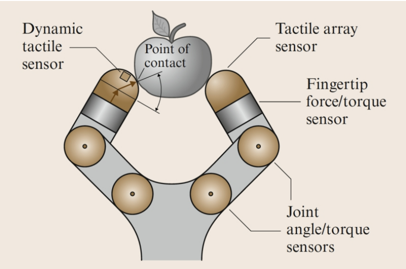

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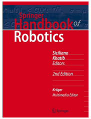

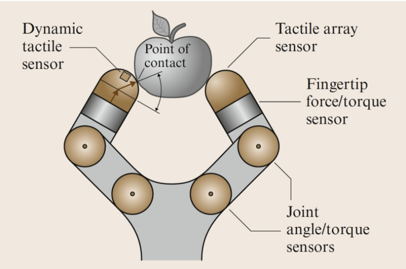

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- Tactile sensors are not (yet) very common on commercial robots (often due to cost)

Ultrasonic Sensors (Sonars)

- A sonar is **an active range sensor that uses ultrasonic sound waves for distance measurement**

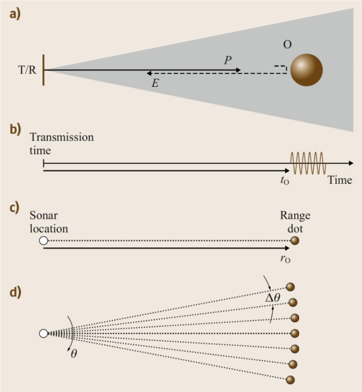

Fig.30.1a–d Sonar ranging principles: **(a)** sonar configuration, **(b)** echo waveform, **(c)** range dot placement, **(d)** sonar map

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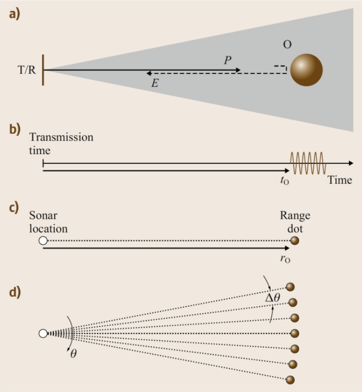

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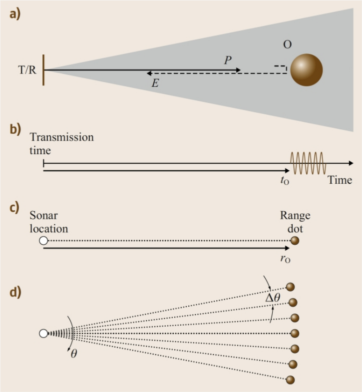

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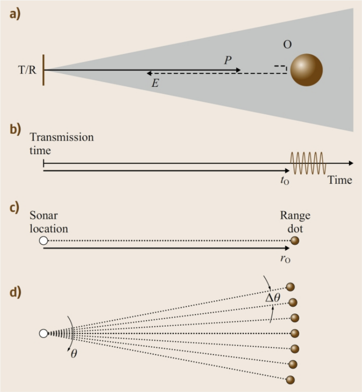

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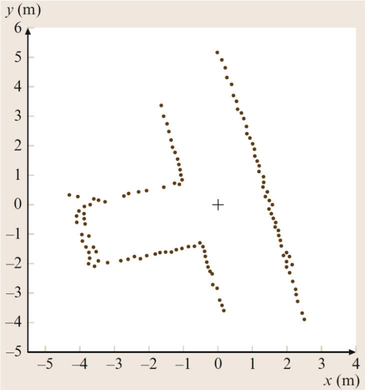
- Sonars are less frequently used on modern mobile platforms, but are commonly applied in underwater robotics

Light Detection and Ranging (Lidar)



Example measurements from a 2D laser scanner

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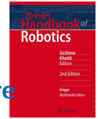

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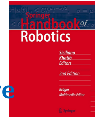

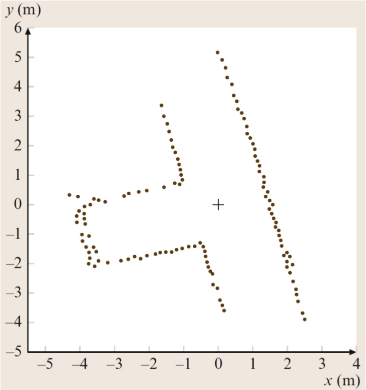

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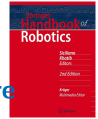

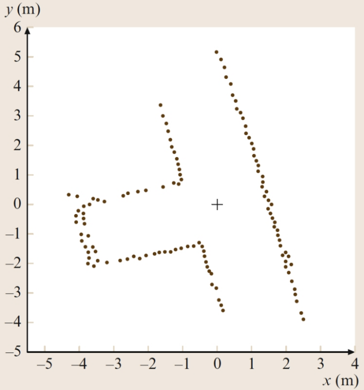

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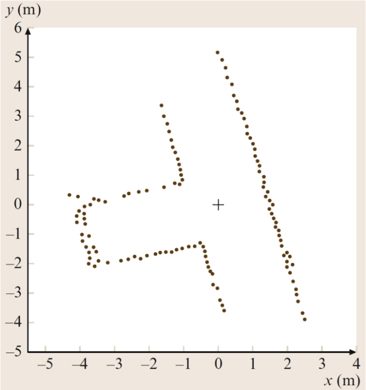

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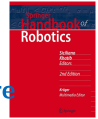

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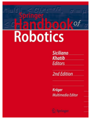
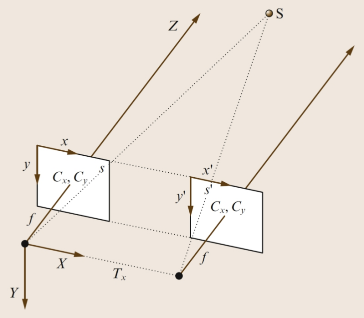
- **Lidars can be two- or three-dimensional**, and typically **return distances to multiple points simultaneously**

Cameras





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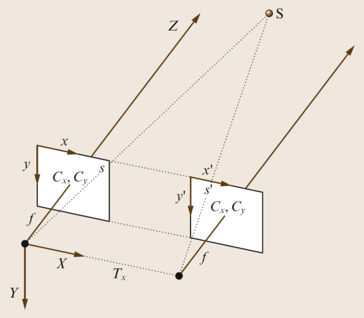
Cameras



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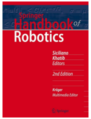

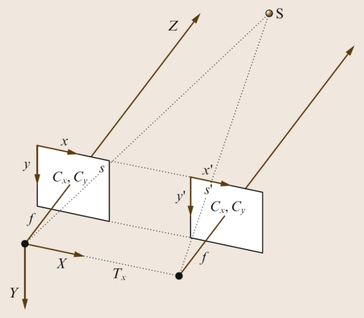

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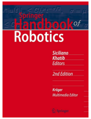

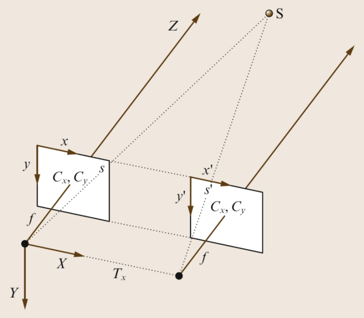

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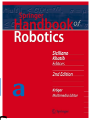
- Visual information captured by cameras is vital for scene understanding

RGB-D Cameras



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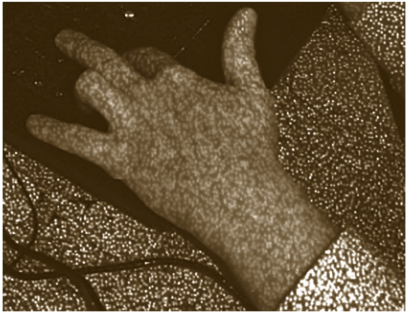

Fig. 31.11 The laser grid of the Kinect for calculating depth

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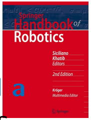

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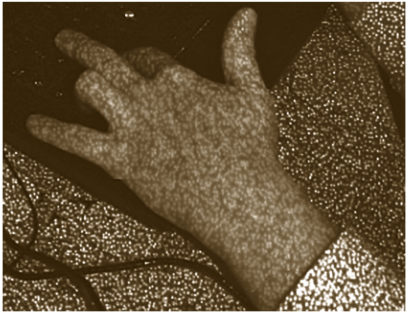

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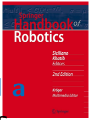

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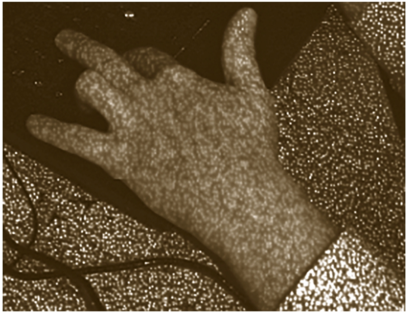

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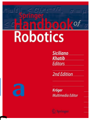

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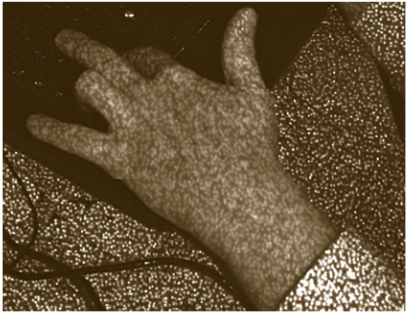

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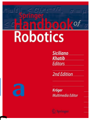

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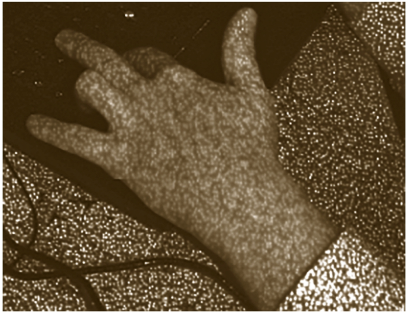
- The set of points measured by an RGB-D camera is usually referred to as a **point cloud**



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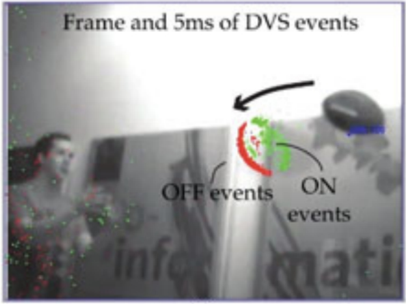
Event Cameras



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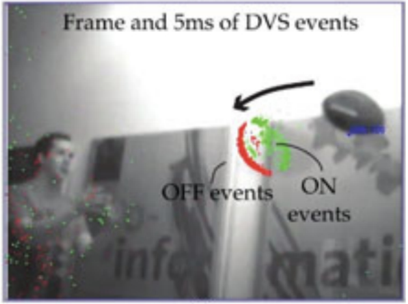

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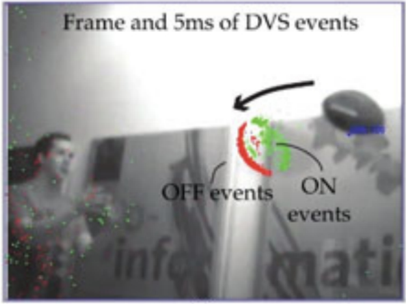

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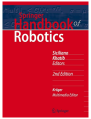
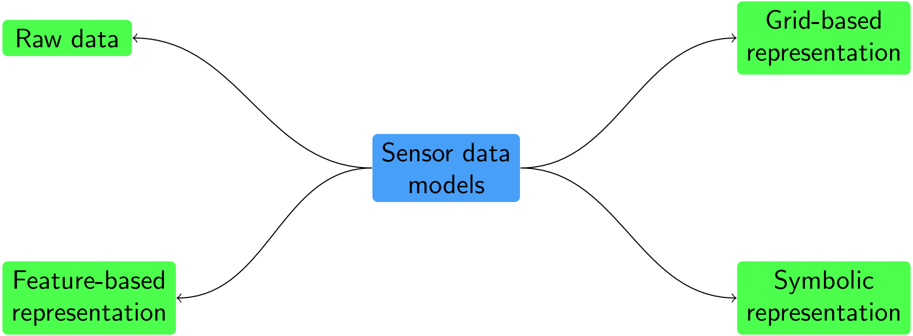
- The design of event cameras is biologically inspired, so event cameras are used in **neuromorphic computing**

Sensor Models

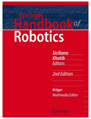
State Representations

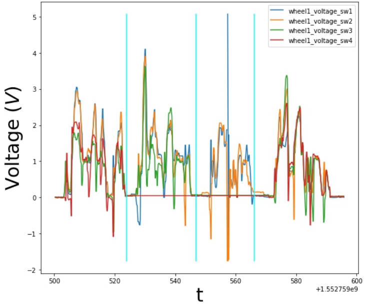


- The purpose of sensor data is to update the robot's representation of itself or the enviroment — **the world's state**
- There are a variety of state representations that are used for different purposes in robotics



Raw Data Representation





Smart wheel voltage measurements (wheels by KELO Robotics GmbH)

- Raw representations **preserve the form of the data as measured by a sensor**

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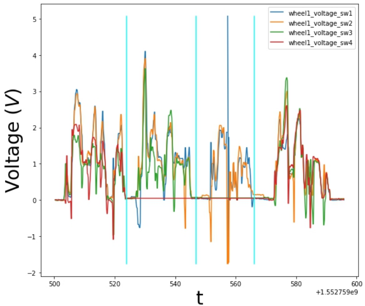

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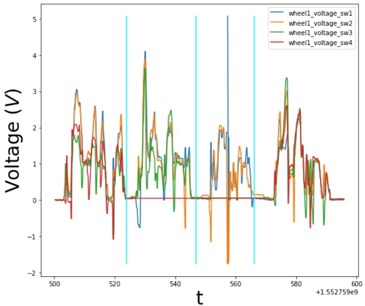

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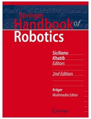
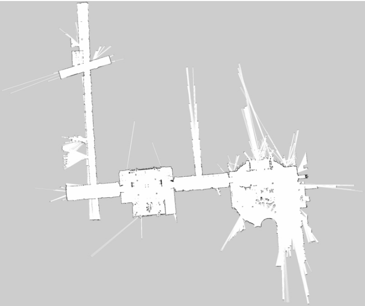
- Raw data is **often used at the low-level robot control level**

Grid-Based Representation





Discrete occupancy grid map (partial map of the ground floor of the H-BRS C-building). White cells denote free space, black cells depict occupied space, and gray cells represent unknown space.

- In a grid-based representation, **data are represented in discrete, non-overlapping cells**

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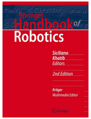

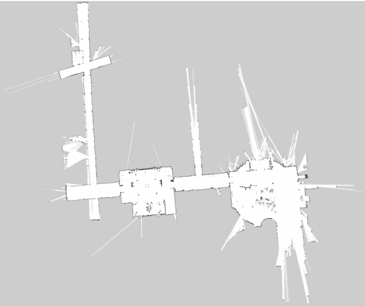

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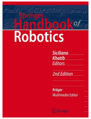

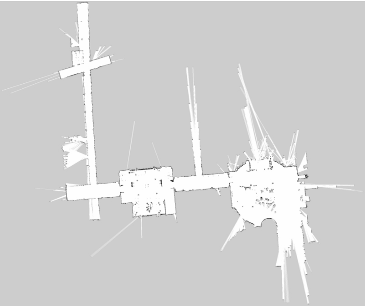

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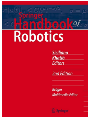

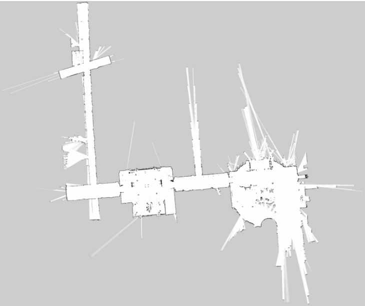

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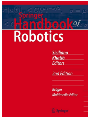
- The discretisation process may potentially **eliminate features in the data that are actually important for a given task**

Feature-Based Representation



Autocorrelation: $\sum_{n \in Z} s(n)\, \overline{s(n-l)}$, where $\overline{s(n-l)}$ is the complex conjugate of $s(n)$, and l is a lag.

Centroid: $\frac{\sum_{i=0}^{N} t_i \times s_i^2}{\sum_i^N s_i^2}$

Mean absolute differences: $mean\left(|\Delta s|\right)$

Mean differences: $mean\left(\Delta s\right)$

Median absolute differences: $median\left(|\Delta s|\right)$

Median differences: $median\left(\Delta s\right)$

Distance: $\sum_{i=0}^{N-1} \sqrt{1 + {\Delta s_i}^2}$

Sum of absolute differences: $\sum_{i=0}^{N-1} |\Delta s_i|$

Total energy: $\frac{\sum_{i=0}^{N} s^2}{t_N - t_0}$

Entropy: $-\sum_{x \in s} P(x) \log_2 P(x)$

Peak to peak distance: $|max(s) - min(s)|$

Area under the curve: $\sum_{i=0}^{N} (t_i - t_{i-1}) \times \frac{s_i + s_{i-1}}{2}$

Examples of features that can be extracted from a time series signal (typically from data windows). M. Barandas et al., "TSFEL: Time Series Feature Extraction Library," *SoftwareX*, vol. 11, pp. 100456: 1–7, 2020.

Features from different layers of a GoogLeNet convolutional neural network (https://distill.pub/2017/feature-visualization/)

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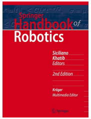

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- **For different modalities, different features are usually of interest** (e.g. frequencies are relevant for time series, but shapes are important for visual data)

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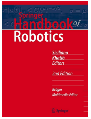

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Entropy: $-\sum_{x \in s} P(x) \log_2 P(x)$

Peak to peak distance: $|max(s) - min(s)|$

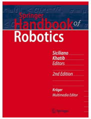
Area under the curve: $\sum_{i=0}^{N} (t_i - t_{i-1}) \times \frac{s_i + s_{i-1}}{2}$

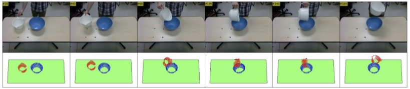
Examples of features that can be extracted from a time series signal (typically from data windows). M. Barandas et al., "TSFEL: Time Series Feature Extraction Library," *SoftwareX*, vol. 11, pp. 100456: 1–7, 2020.

Features from different layers of a GoogLeNet convolutional neural network (https://distill.pub/2017/feature-visualization/)

- In a variety of application, **sensor data are summarised by various features** (e.g. lines can be extracted from laser measurements)
- **For different modalities, different features are usually of interest** (e.g. frequencies are relevant for time series, but shapes are important for visual data)
- Depending on the application and the knowledge about the underlying data process, **features can be manually designed** (illustrated on the top left) or **learned** (illustrated on the bottom left)

Qualitative Representation





Example of using point clouds for estimating spatial object relations. K. Zampogiannis et al., "Learning the Spatial Semantics of Manipulation Actions through Preposition Grounding," in *Proc. IEEE Int. Conf. Robotics and Automation (ICRA)*, 2015, pp. 1389–1396.

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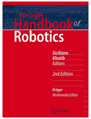

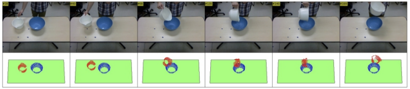

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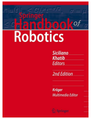

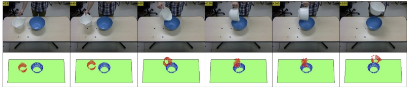

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- **Qualitative representations attach semantic meaning to sensor data**

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There are a number of values that can be used to characterise the operation of a sensor

Resolution

Smallest possible difference between two values that can be measured by a sensor

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Accuracy and Precision

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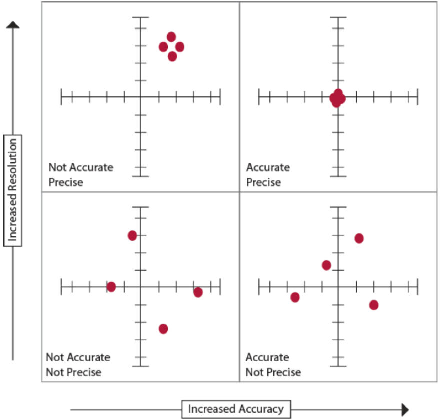

https://allsensors.com/engineering-resources/white-papers/accuracy-and-precision-for-mems-pressure-sensors

Sensor Errors

There are two main types of sensor errors that we can distinguish:

Systematic errors

Occur at regular intervals or as fixed value offsets; have a clear regularity pattern that can be accounted for

Systematic errors can be identified and corrected, typically by sensor calibration or online reconfiguration

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Random errors

Occur sporadically without any apparent regularity, often due to environmental influences that are difficult to account for

Random errors cannot be corrected for, but can be modelled, usually by a Gaussian distribution $\mathcal{N}(\boldsymbol{\mu}, \Sigma)$

Sensor Modelling Process

To use a sensor for estimating a given physical quantity of interest, a variety of steps need to be performed as part of a **sensor modelling process**:

Creating a physical sensor model

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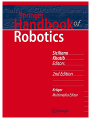

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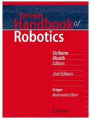

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Identifying conditions under which the sensor fails

Creating a Physical Model

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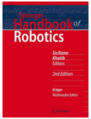

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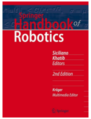

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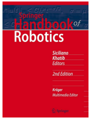
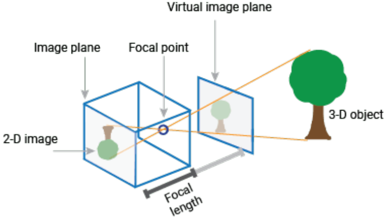
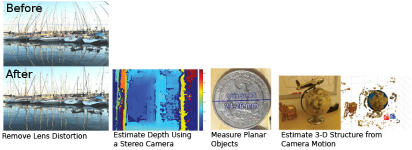
- This relationship does not have to be a direct one, but can involve intermediate feature extraction and processing

Sensor Calibration





A model of a pinhole camera



Benefits of calibrated cameras

https://www.mathworks.com/help/vision/ug/camera-calibration.html

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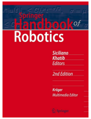

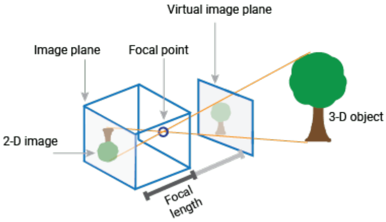

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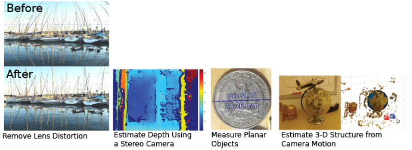

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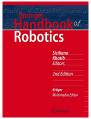

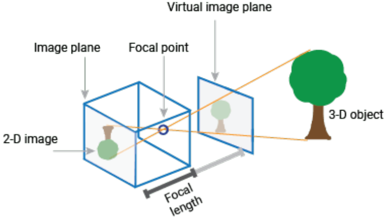

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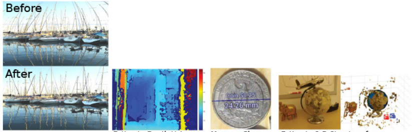

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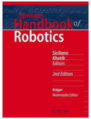
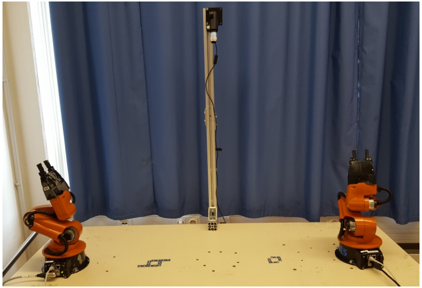
- Calibration is particularly important to perform for cameras, whose models involves multiple parameters (camera center, focal length, distortion parameters) that need to be accounted for

Sensor Error Modelling





A setup for estimating positions of placed objects with a camera in one of our labs. Here, the error model is estimated by manually measuring object positions.

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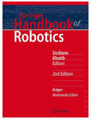

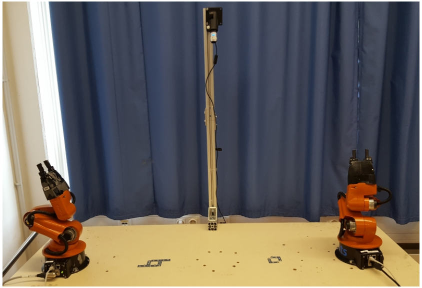

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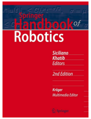

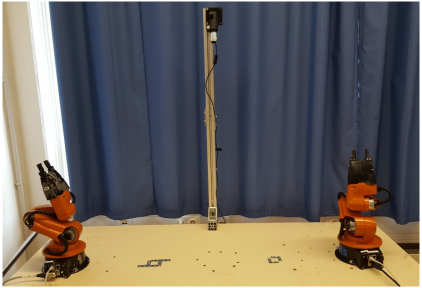

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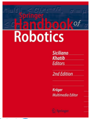
- The estimation of an error model usually **needs to be done in controlled conditions**, where the ground-truth values can be accurately estimated

Identifying Failure Conditions



A laser scanner cannot detect glass surfaces; thus, a robot using a laser scanner has troubles recognising the glass door of our university.

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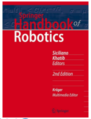

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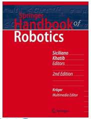

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- **Relying on incorrect sensor data can lead to task failures** (e.g. a robot cannot see an object of interest) or **introduce undesired conditions for a robot** (e.g. collisions with obstacles)
- Regardless of the sensor, it is thus **essential to have knowledge of a sensor's failure cases so that the errors can be mitigated** (e.g. by relying on a different sensor under given environment conditions)
  - But it is often challenging to foresee all possible failure modes