Principles of Robot Autonomy I

Robotic sensors and introduction to computer vision

Stanford University

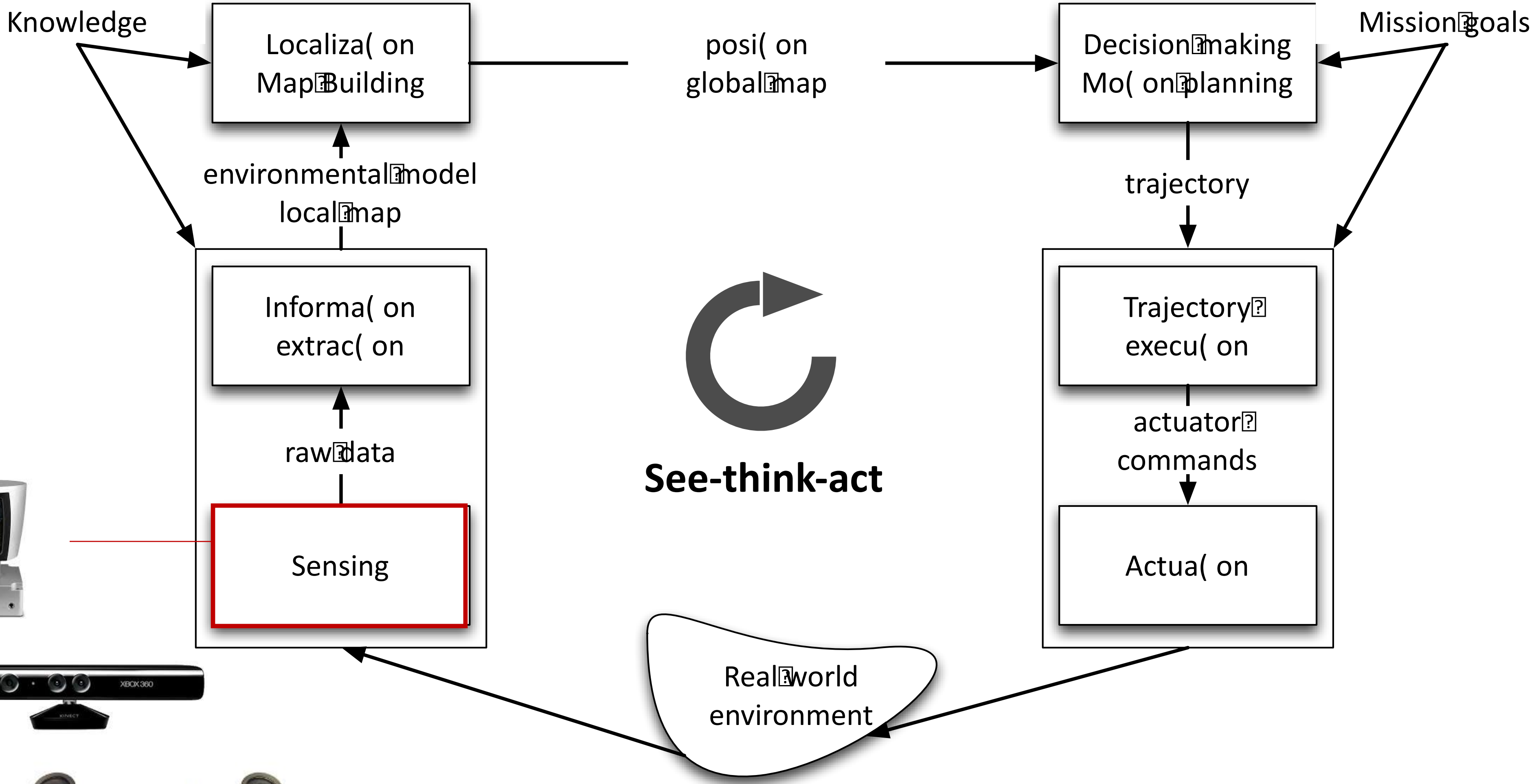
Autonomous Systems Lab

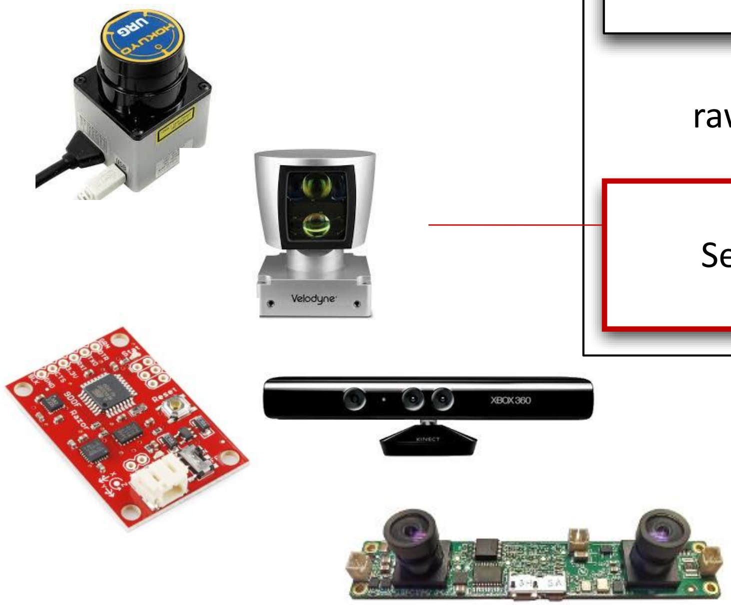
Agenda

- Agenda
  - Overview of key performance characteristics for robotic sensors
  - Overview of main sensors for robot autonomy, e.g. proprioceptive / exteroceptive, passive / active
  - Intro to computer vision

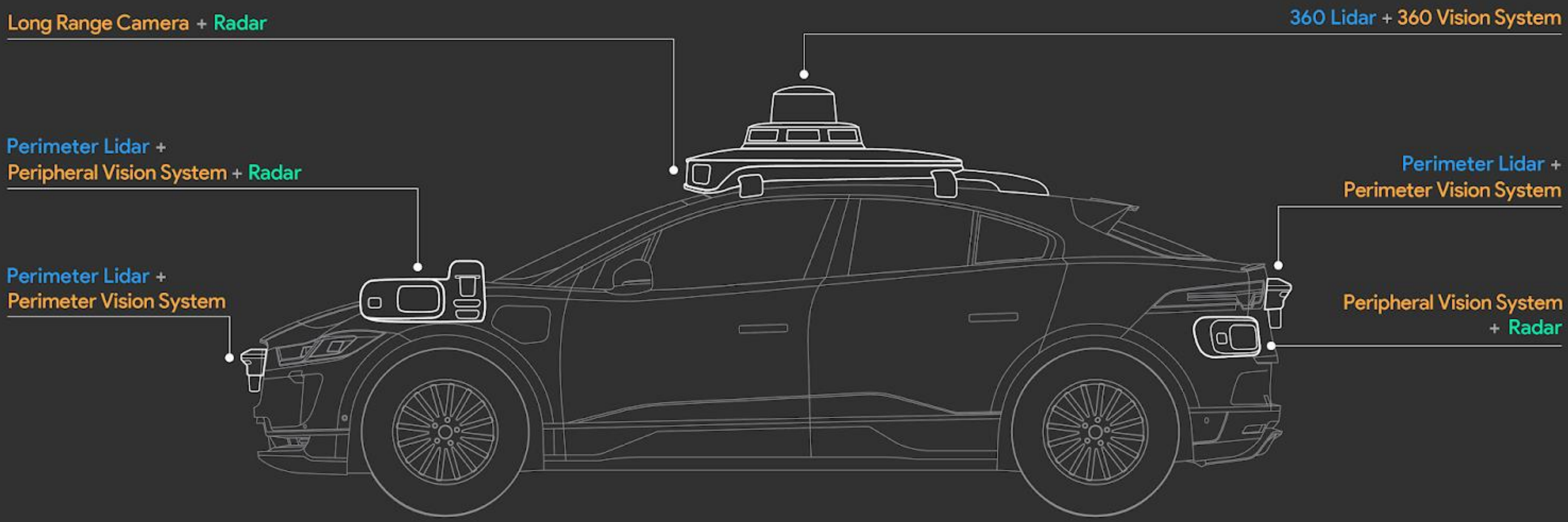
- Readings:
  - Chapters 7 and 8.1 in PoRA lecture notes

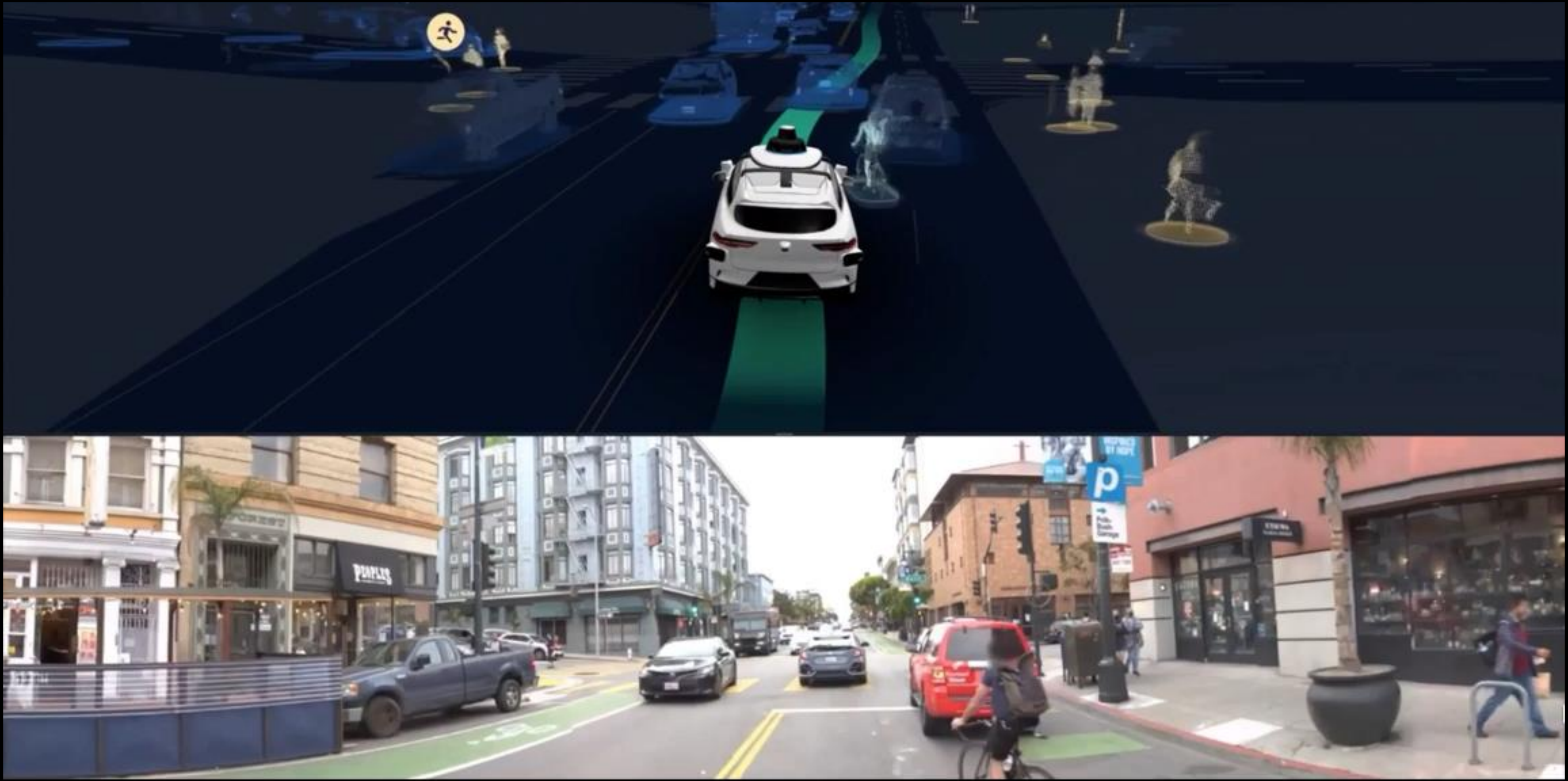
Sensors for mobile robots





Example: self-driving cars





Classification of sensors

- Proprioceptive: measure values internal to the robot
  - E.g.: motor speed, robot arm joint angles, and battery voltage
- Exteroceptive: acquire information from the robot's environment
  - E.g.: distance measurements and light intensity

- Passive: measure ambient environmental energy entering the sensor
  - Challenge: performance heavily depends on the environment
  - E.g.: temperature probes and cameras
- Active: emit energy into the environment and measure the reaction
  - Challenge: might affect the environment
  - E.g.: ultrasonic sensors and laser rangefinders

Sensor performance: design specs

- Dynamic range: ratio between the maximum and minimum input values (for normal sensor operation)
- Resolution: minimum difference between two values that can be detected by a sensor
- Linearity: whether or not the sensor's output response depends linearly on the input
- Bandwidth or frequency: speed at which a sensor provides readings (in Hertz)

Sensor performance: in situ specs

- Sensitivity: ratio of output change to input change
- Cross-sensitivity: sensitivity to quantities that are unrelated to the target quantity
- Error: difference between the sensor output m and the true value v

$$\text{error} \coloneqq m - v$$

- Accuracy: degree of conformity between the sensor's measurement and the true value

$$\text{accuracy} \coloneqq 1 - |\text{error}|/v$$

- Precision: reproducibility of the sensor results

Sensor errors

- Systematic errors: caused by factors that can in theory be modeled; they are deterministic
  - E.g.: calibration errors
- Random errors: cannot be predicted with sophisticated models; they are stochastic
  - E.g.: spurious range-finding errors
- Error analysis: performed via a probabilistic analysis
  - Common assumption: symmetric, unimodal (and often Gaussian) distributions; convenient, but often a coarse simplification
  - Error propagation characterized by the *error propagation law*

An ecosystem of sensors

- Encoders
- Heading sensors
- Accelerometers and IMU
- Beacons
- Active ranging
- Cameras

Encoders

- Encoder: an electro-mechanical device that converts motion into a sequence of digital pulses, which can be converted to relative or absolute position measurements
    - proprioceptive sensor
    - can be used for robot localization

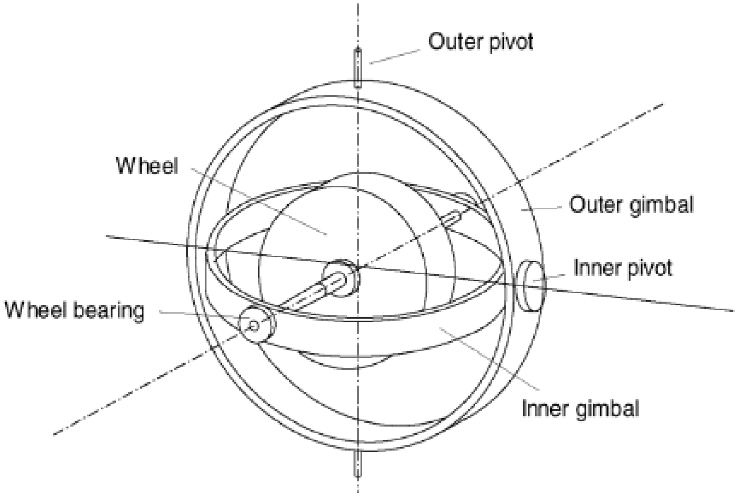
- Fundamental principle of optical encoders: use a light shining onto a photodiode through slits in a metal or glass disc

Wheel encoder
Credit: Pololu

Credit: Honest Sensor

Heading sensors

- Used to determine robot's orientation, it can be:
  1. Proprioceptive, e.g., gyroscope (heading sensor that preserves its orientation in relation to a fixed reference frame)
  2. Exteroceptive, e.g., compass (shows direction relative to the geographic cardinal directions)
- Fusing measurements with velocity information, one can obtain a position estimate (via integration) -> *dead reckoning*
- Fundamental principle of mechanical gyroscopes: angular momentum associated with spinning wheel keeps the axis of rotation inertially stable



Credit: SNS

Accelerometer and IMU

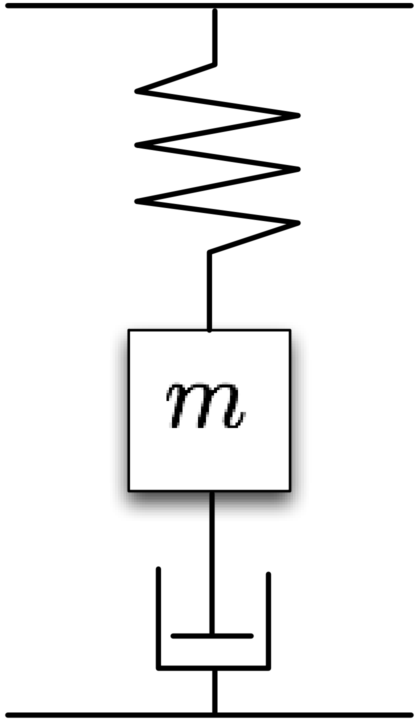
- Accelerometer: device that measures all external forces acting upon it
- Mechanical accelerometer: essentially, a spring-mass-damper system

$$F_{\text{applied}} = m\ddot{x} + c\dot{x} + kx$$

with *m* mass of proof mass, *c* damping coefficient, *k* spring constant; in steady state

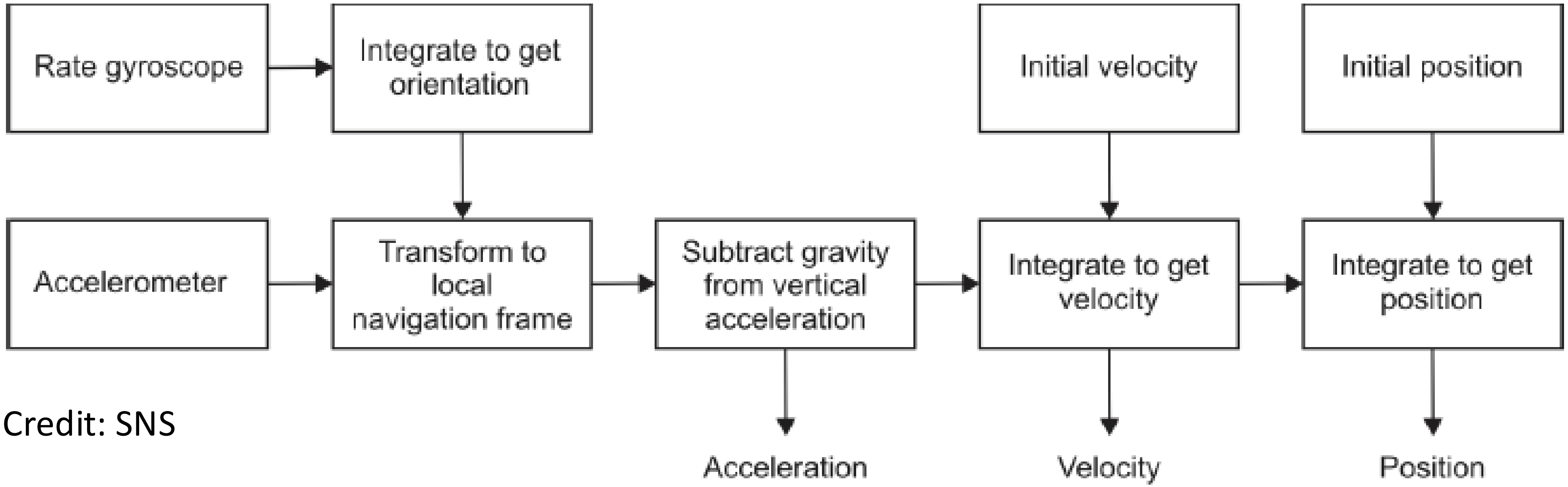
$$a_{\text{applied}} = \frac{kx}{m}$$

- Modern accelerometers use MEMS (cantilevered beam + proof mass); deflection measured via *capacitive* or *piezoelectric* effects



Inertial Measurement Unit (IMU)

- Definition: device that uses gyroscopes and accelerometers to estimate the relative position, orientation, velocity, and acceleration of a moving vehicle with respect to an inertial frame
- *Drift* is a fundamental problem: to cancel drift, periodic references to external measurements are required



Credit: SNS

Beacons

- Definition: signaling devices with precisely known positions
- Early examples: stars, lighthouses
- Modern examples: GPS, motion capture systems

Active ranging

- Provide direct measurements of distance to objects in vicinity
- Key elements for both localization and environment reconstruction
- Main types:
    1. Time-of-flight active ranging sensors (e.g., ultrasonic and laser rangefinder)

Credit: https://electrosome.com/hc-sr04-ultrasonic-sensor-pic/

    2. Geometric active ranging sensors (optical triangulation and structured light)

Time-of-flight active ranging

- Fundamental principle: time-of-flight ranging makes use of the propagation of the speed of sound or of an electromagnetic wave
- Travel distance is given by

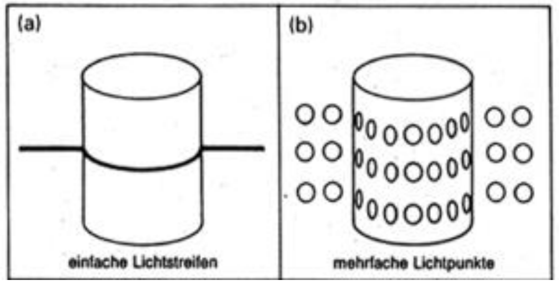
$$d = c\,t$$

where *d* is the distance traveled, *c* is the speed of the wave propagation, and *t* is the time of flight

- Propagation speeds:
  - Sound: 0.3 m/ms
  - Light: 0.3 m/ns
- Performance depends on several factors, e.g., uncertainties in determining the exact time of arrival and interaction with the target

Geometric active ranging

- Fundamental principle: use geometric properties in the measurements to establish distance readings
- The sensor projects a known light pattern (e.g., point, line, or texture); the reflection is captured by a receiver and, together with known geometric values, range is estimated via triangulation
- Examples:
  - Optical triangulation (1D sensor)
  - Structured light (2D and 3D sensor)



Credit: Matt Fisher

Several other sensors are available

- Classical, e.g.:
  - Radar (possibly using Doppler effect to produce velocity data)
  - Tactile sensors

- Emerging technologies:
  - Artificial skins
  - Neuromorphic cameras

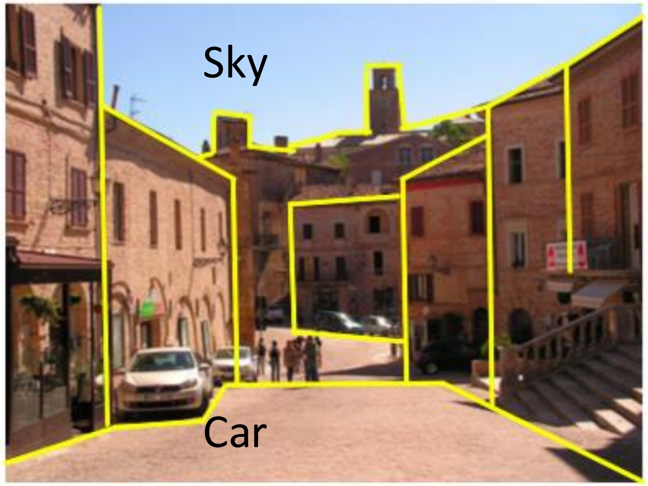
Introduction to computer vision

- Aim
  - Learn about cameras and camera models
  - Learn about the outputs of perception and what they might be used for

- Readings
  - Siegwart, Nourbakhsh, Scaramuzza. Introduction to Autonomous Mobile Robots. Section 4.2.3.
  - D. A. Forsyth and J. Ponce [FP]. Computer Vision: A Modern Approach (2nd Edition). Prentice Hall, 2011. Chapter 1.
  - R. Hartley and A. Zisserman [HZ]. Multiple View Geometry in Computer Vision. Academic Press, 2002. Chapter 6.1.

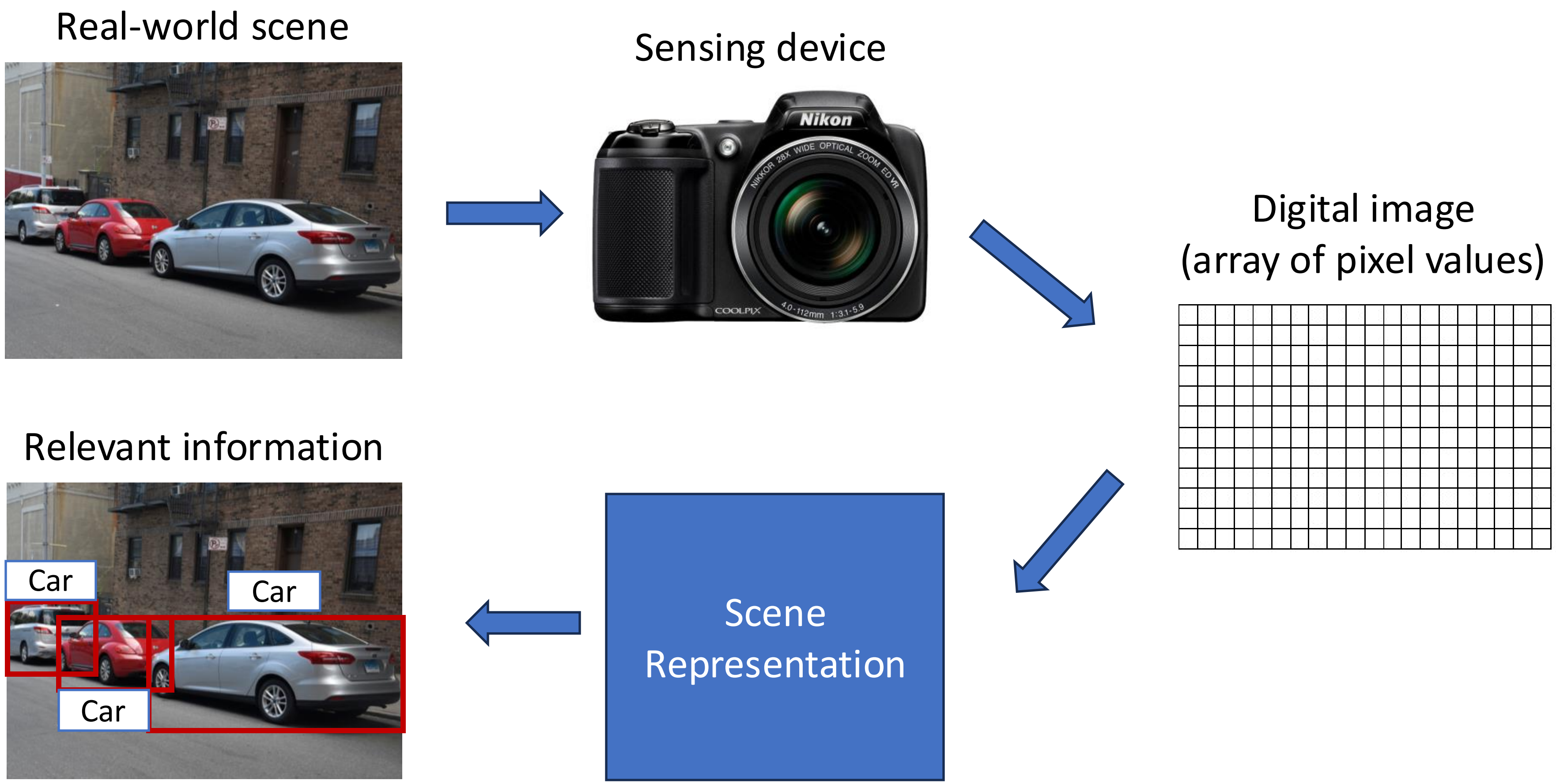
Vision

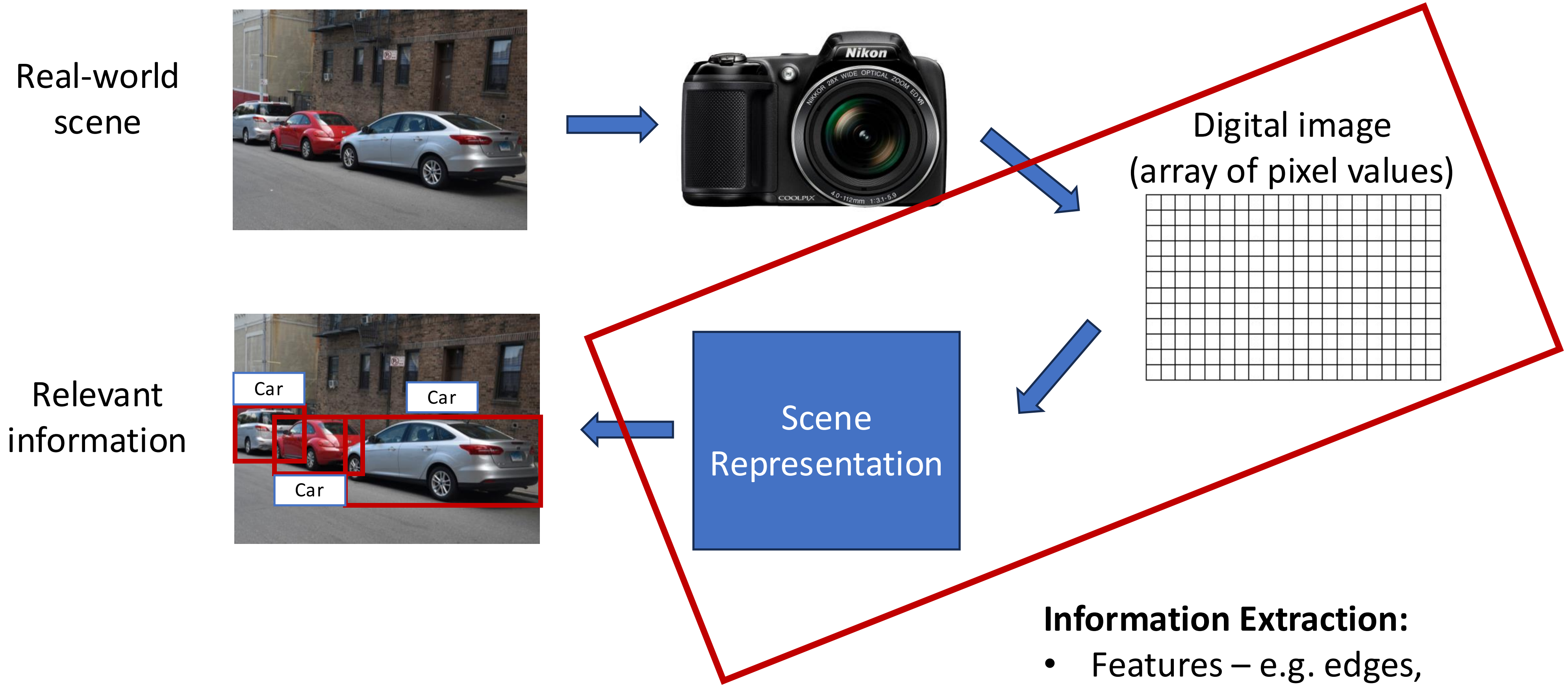
- Vision: ability to interpret the surrounding environment using light in the visible spectrum reflected by objects in the environment
- Human eye: provides enormous amount of information, ~millions of bits per second
- Cameras (e.g., CCD, CMOS): capture light -> convert to digital image -> process to get relevant information (from geometric to semantic)



1. Information extraction
2. Interpretation

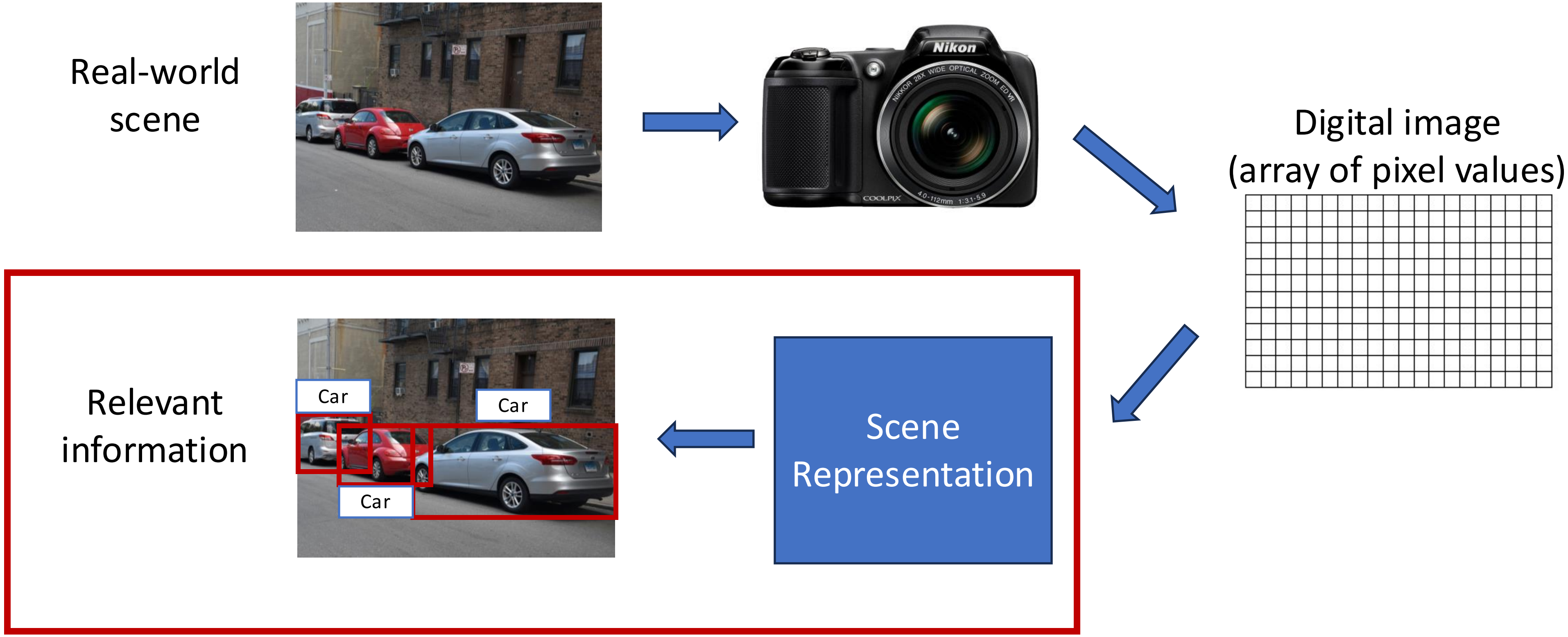
Computer Vision Pipeline





Information Extraction:

- Features – e.g. edges, corners, texture, colors, etc.
- 3D structure



Interpretation:

- Object detection
- Object tracking
- Image registration
- Image segmentation

Object Detection

- Goal: Detect instances of semantic objects of a certain class
    - E.g. pedestrian detection, face detection
- Approaches:
    - Traditional methods, e.g.:
        - Scale-invariant feature transform (SIFT)
        - Histogram of Oriented Gradients (HOG)
    - Learning-based:
        - Using region proposals
        - Without region proposals: You Only Look Once (YOLO), Single Shot Detector (SSD)

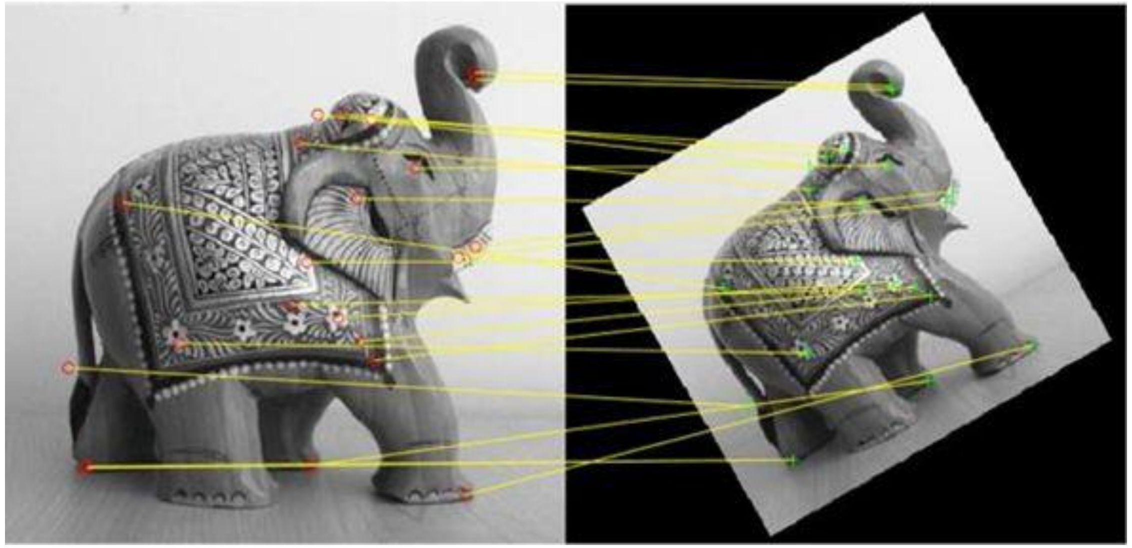
Object Tracking

- Goal: Follow and locate a specific object across a sequence of images or video frames
- Applications: Autonomous driving, surveillance, augmented reality, medical imaging, sports analysis, etc.
- Approaches:
  - Traditional methods, e.g. mean-shift tracking or Kalman filters
  - Learning-based methods, e.g. Siamese networks or recurrent neural networks (RNNs)

Image Registration

- Goal: Transform different sets of data into one coordinate system
- Examples:
  - Data from multiple photographs (e.g. with different viewpoints)
  - Data from different sensors (e.g. LIDAR and RGB camera)

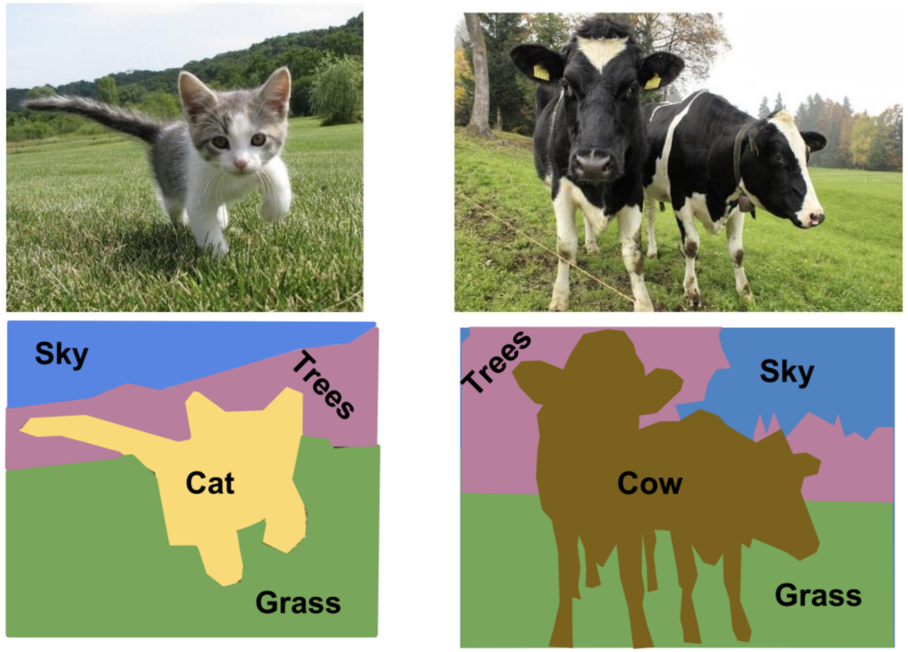
Source: [Mathworks]



Example of LIDAR-camera registration shown in Notebook 9!

Image Segmentation

- Semantic segmentation:
    - Label each pixel in the image with a category label
    - Doesn’t differentiate instances, only cares about pixels



- Instance segmentation:
    - Label each pixel with its object instance
    - Identifies individual objects within each category

Source:
Stanford CS 231n
lecture slides

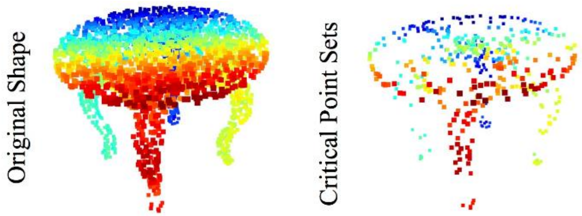
Information extraction and interpretation can also be done with LIDAR data!

Point cloud

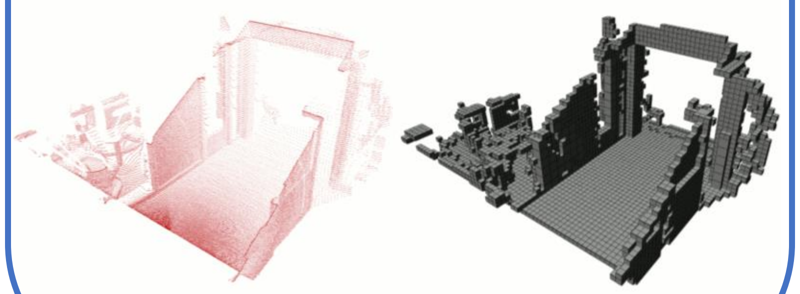
Images from [PointNet] and [OctoMap]

Features

Critical points

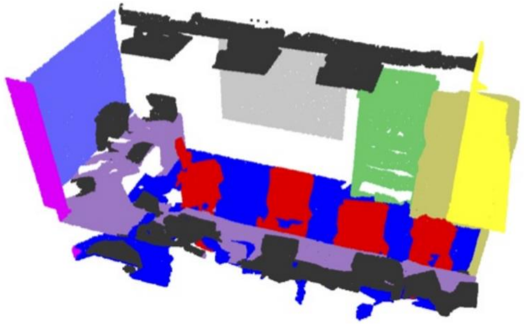


Occupancy grid map

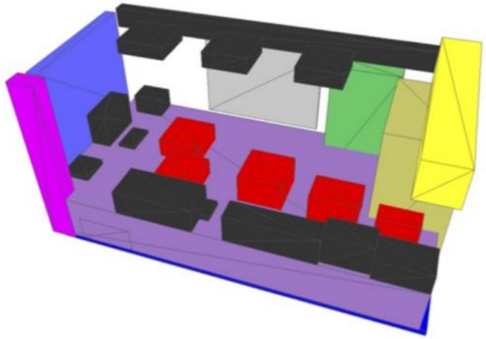


Tasks

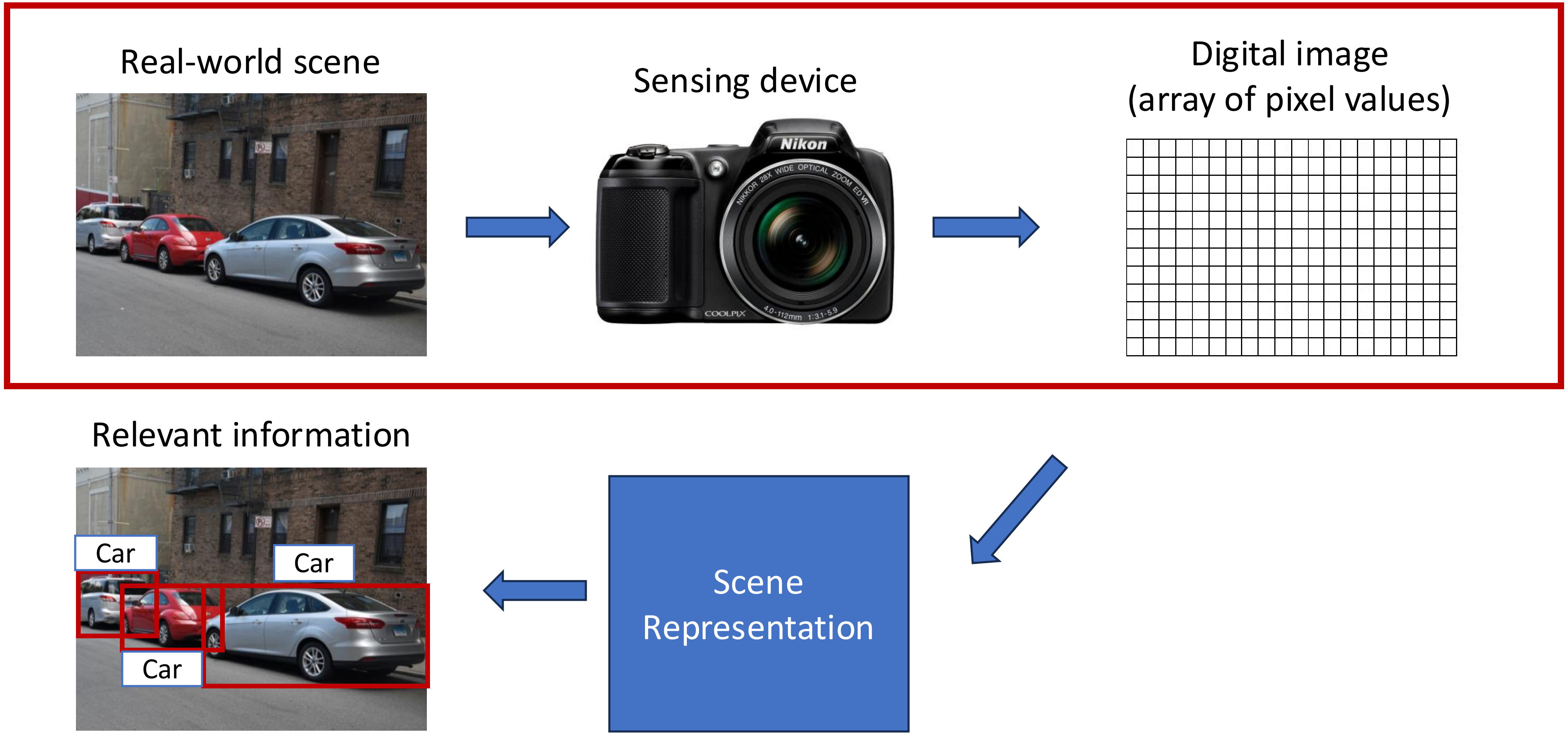
Semantic segmentation



Object detection

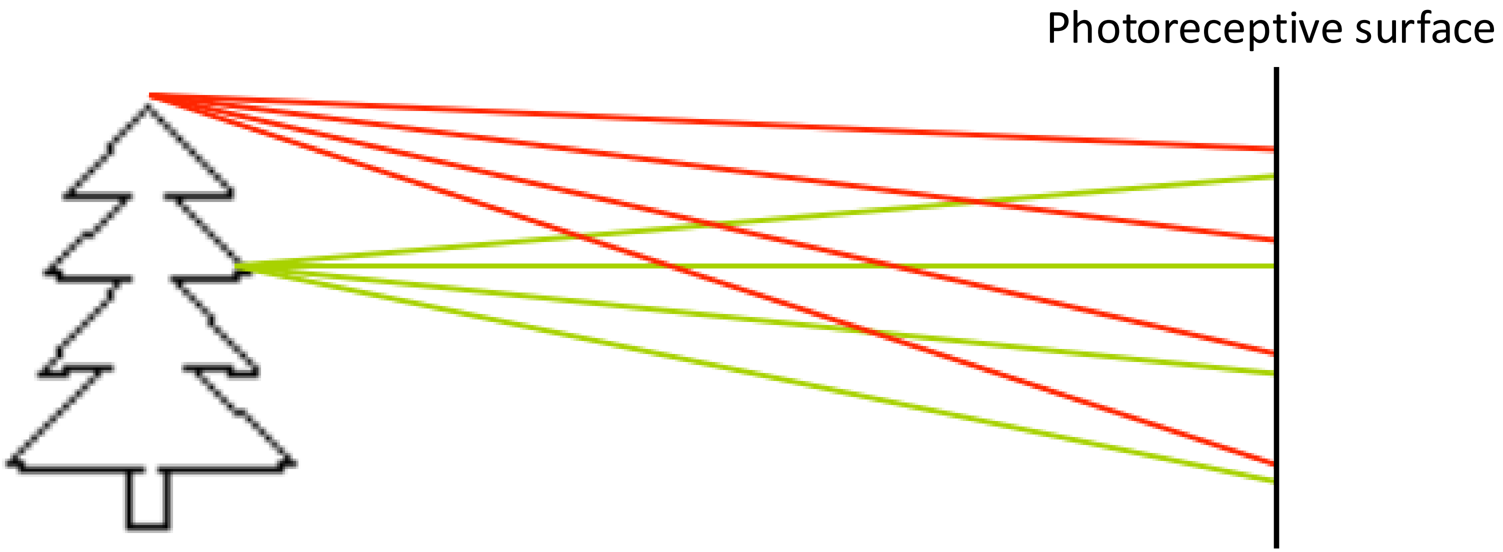


From Scenes to Digital Images



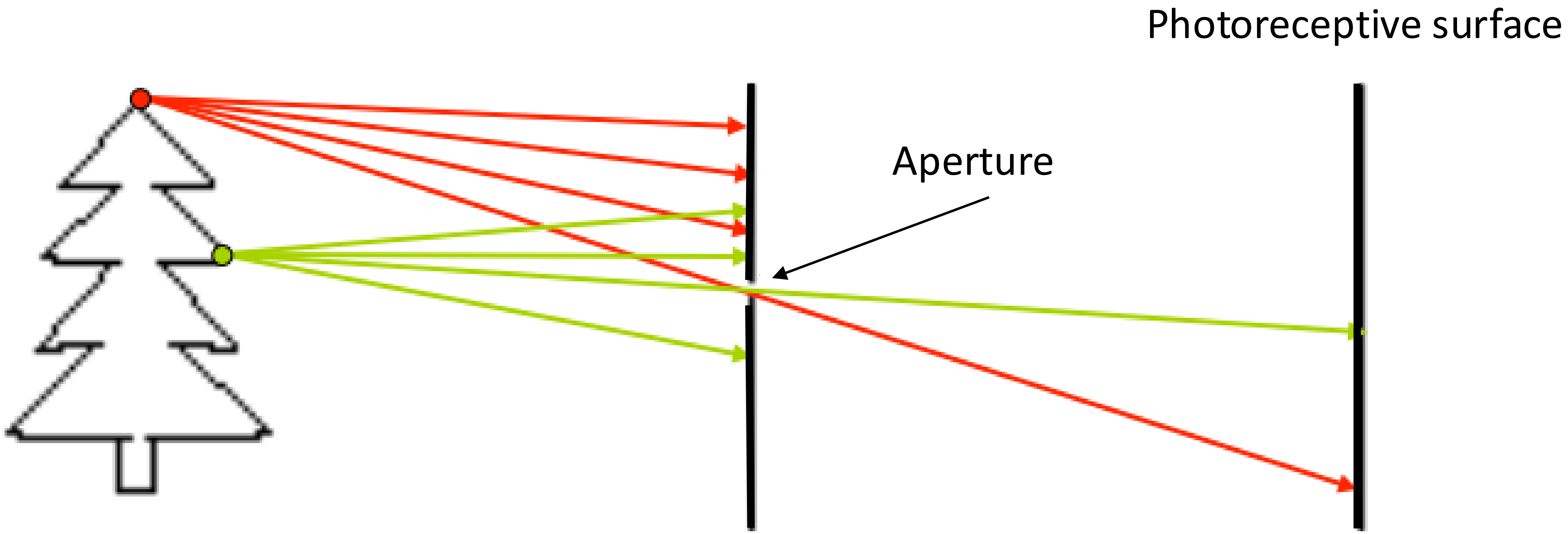
How to capture an image of the world?

- Light is reflected by the object and scattered in all directions
- If we simply add a photoreceptive surface, the captured image will be extremely blurred



Pinhole camera

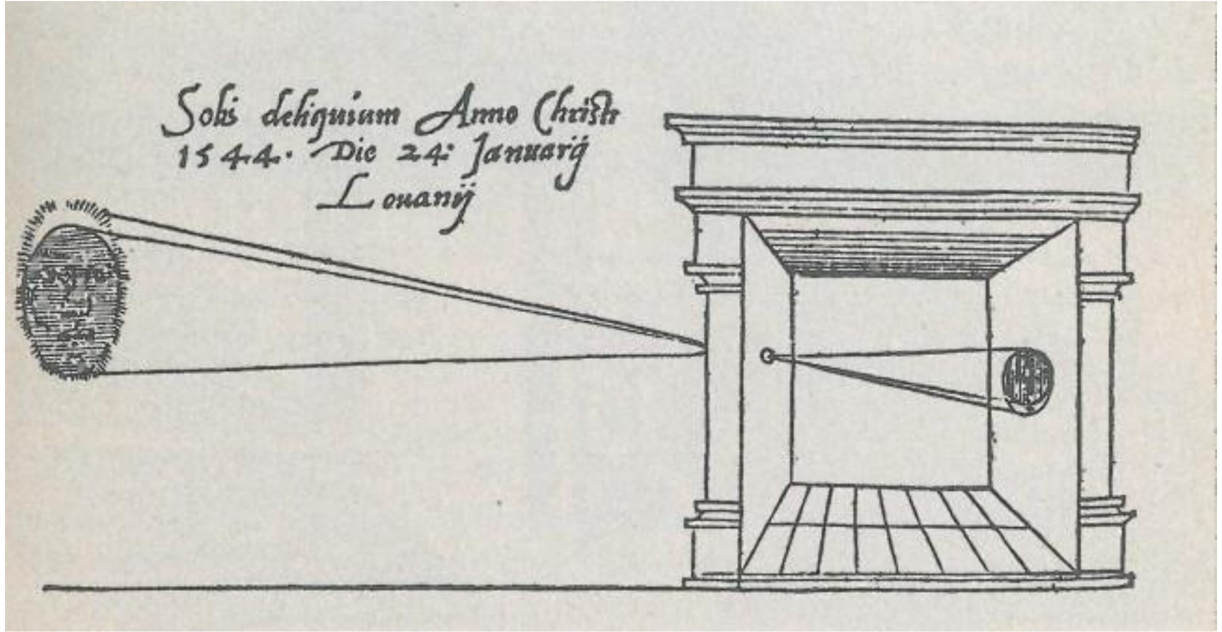
- Idea: add a barrier to block off most of the rays



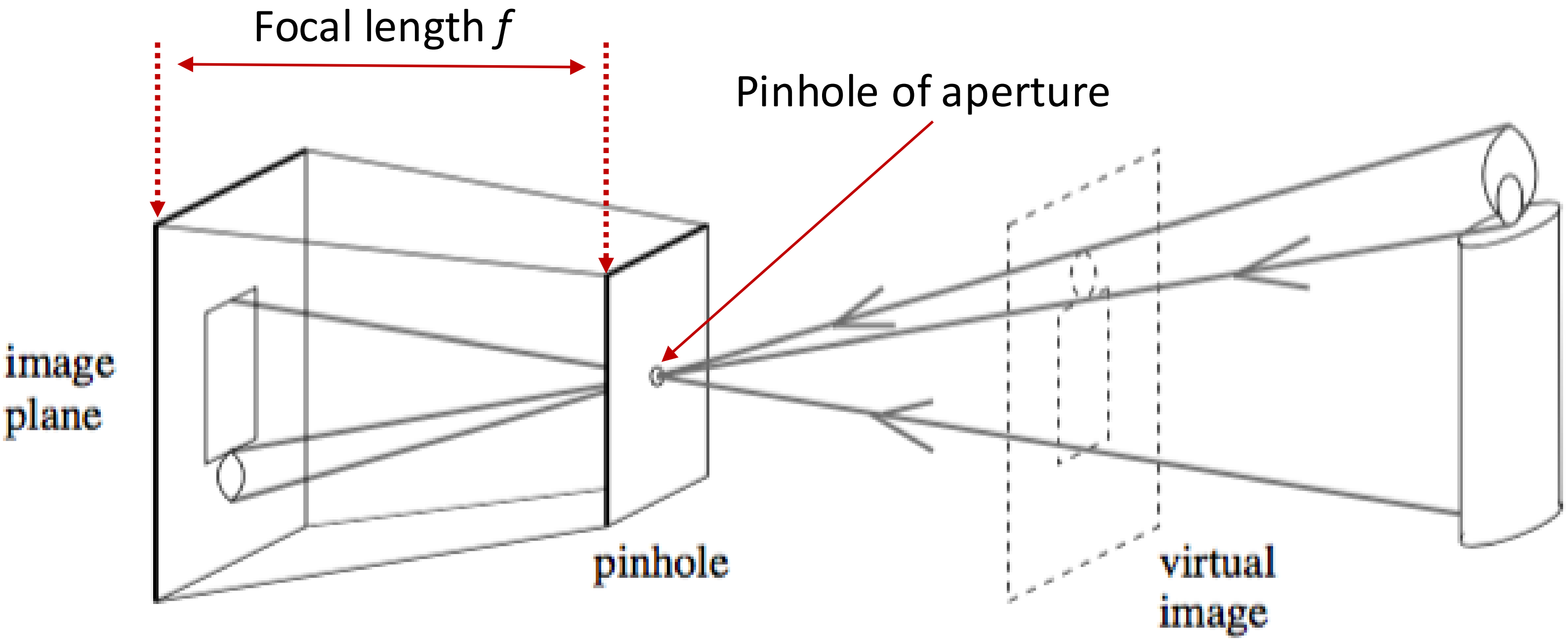
- Pinhole camera: a camera *without a lens* but with a tiny aperture, a *pinhole*

A long history

- Very old idea (several thousands of years BC)
- First clear description from Leonardo Da Vinci (1502)
- Oldest known published drawing of a camera obscura by Gemma Frisius (1544)



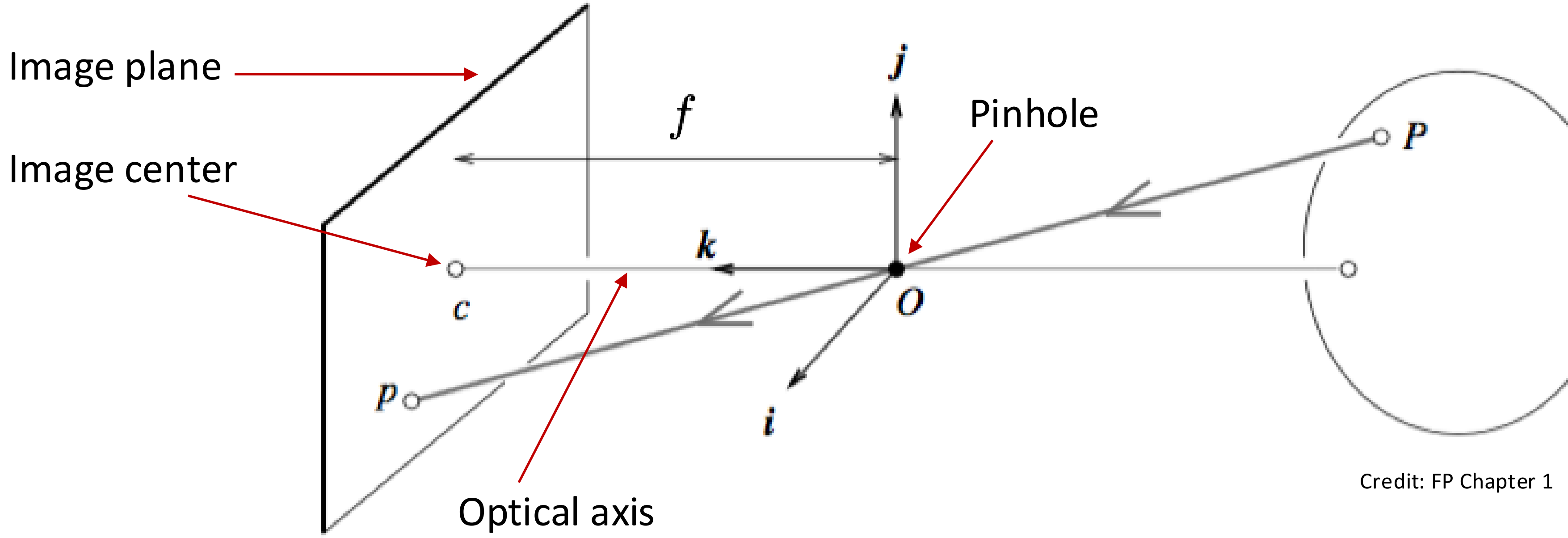
Pinhole camera



Credit: FP Chapter 1

- Perspective projection creates inverted images
- Sometimes it is convenient to consider a *virtual image* associated with a plane lying in front of the pinhole
- Virtual image not inverted but otherwise equivalent to the actual one

Pinhole perspective



$$P = (X, Y, Z)$$

Perspective

$$p = (x, y, z)$$

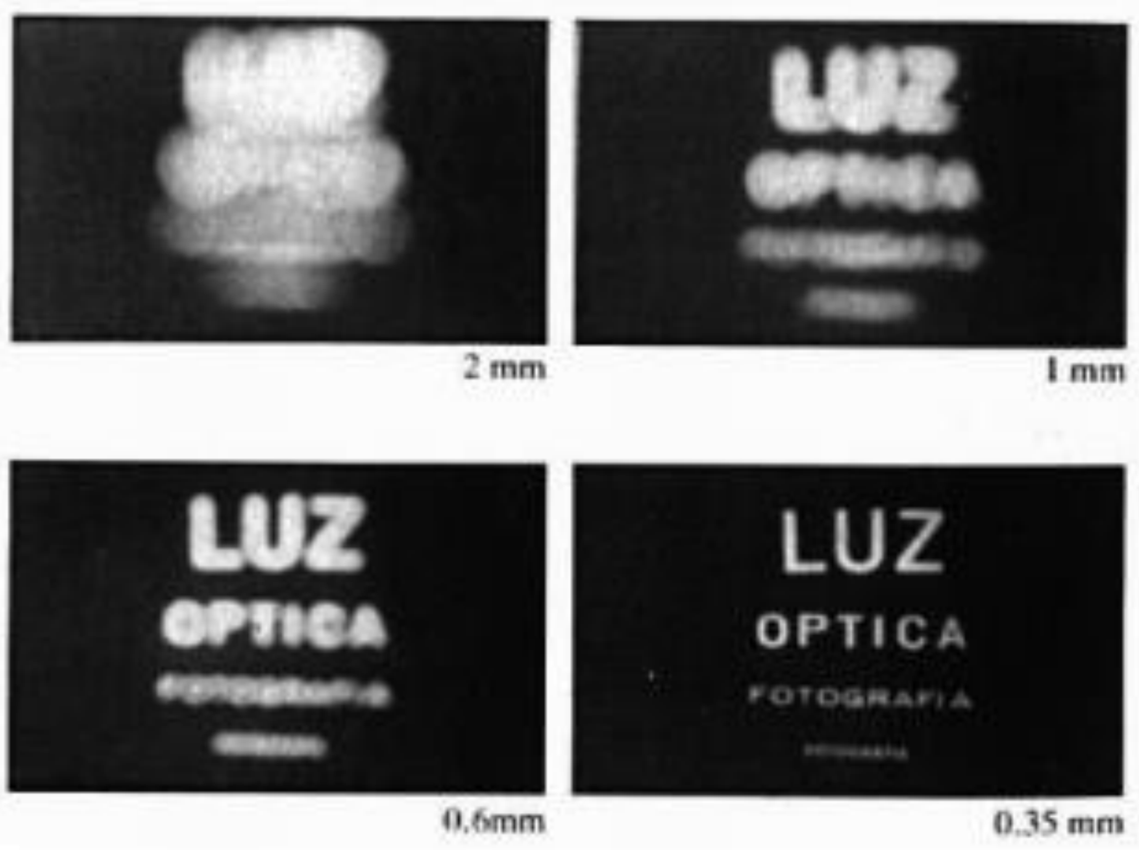
- Since P, O, and p are collinear: $\overline{Op} = \lambda \overline{OP}$ for some $\lambda \in R$
- Also, z=f, hence

$$\begin{cases} x = \lambda X \\ y = \lambda Y \\ z = \lambda Z \end{cases} \Leftrightarrow \lambda = \frac{x}{X} = \frac{y}{Y} = \frac{z}{Z} \quad \Rightarrow \quad \begin{cases} x = f\,\frac{X}{Z} \\ y = f\,\frac{Y}{Z} \end{cases}$$

Issues with pinhole camera

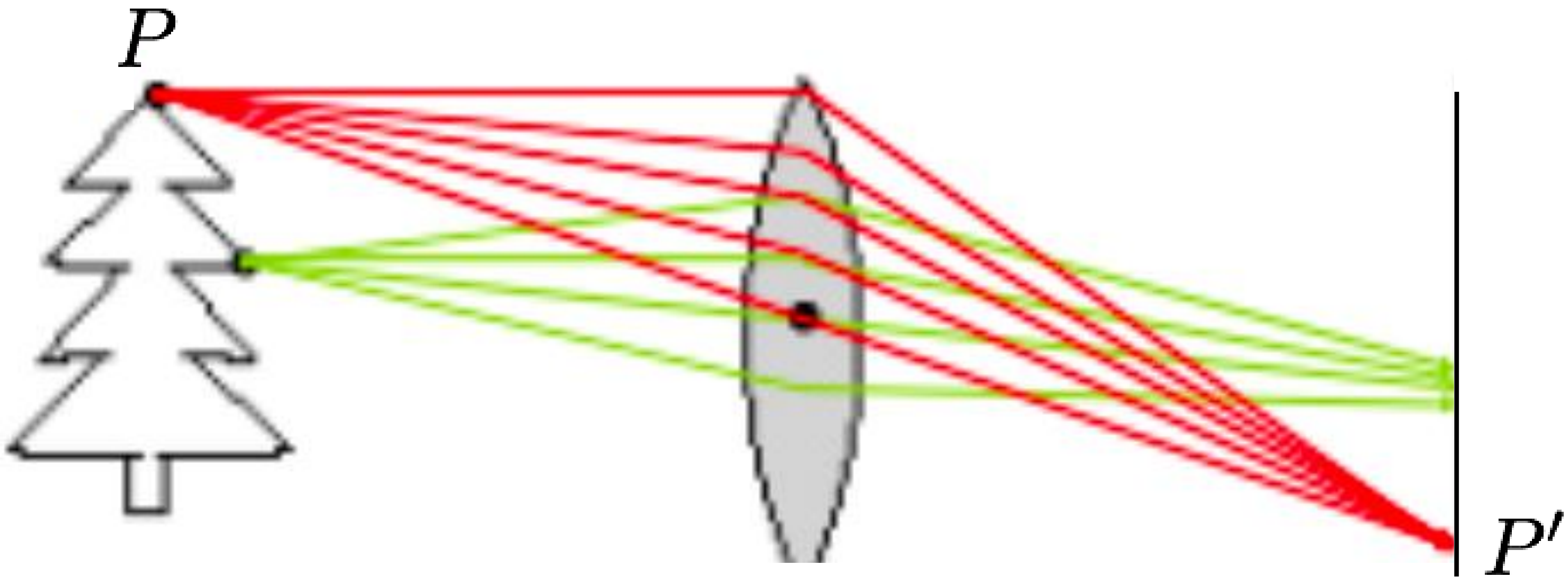
- Larger aperture -> greater number of light rays that pass through the aperture -> blur
- Smaller aperture -> fewer number of light rays that pass through the aperture -> darkness (+ diffraction)

- Solution: add a lens to replace the aperture!



Lenses

- Lens: an optical element that focuses light by means of refraction



Next time: camera models & calibration