



AUSROS

Australian School of Robotic Systems

A1 - Sensors

AUSROS 2024
Donald Dansereau

Understanding Sensors : Why Sense?



<https://www.youtube.com/watch?v=g0TaYhipOfo>

Examples of Sensors



Infrared range



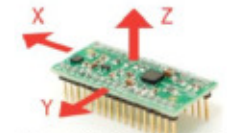
Ultrasonic range



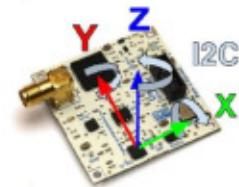
Inertial measurement unit (IMU)



Magnetometer / Compass



Accelerometer



Gyro



Passive infrared (PIR) motion



Line sensor



Camera



IR Temperature



Micro load cell



RADAR



RGBD Camera



Force sensing resistor



Depth/Pressure



Photoresistor



Push Button



Scanning LiDAR (2D)



Scanning LiDAR (3D)



Temperature



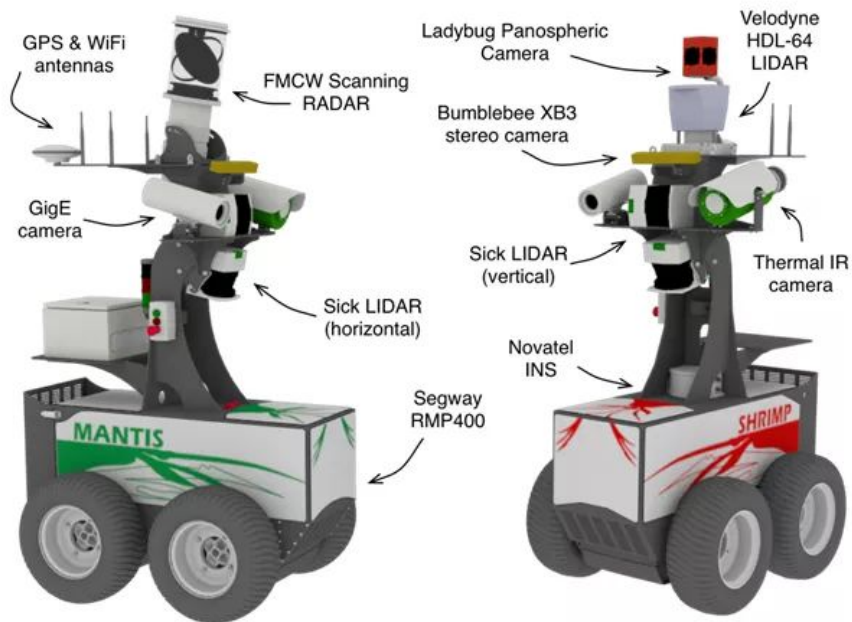
GPS



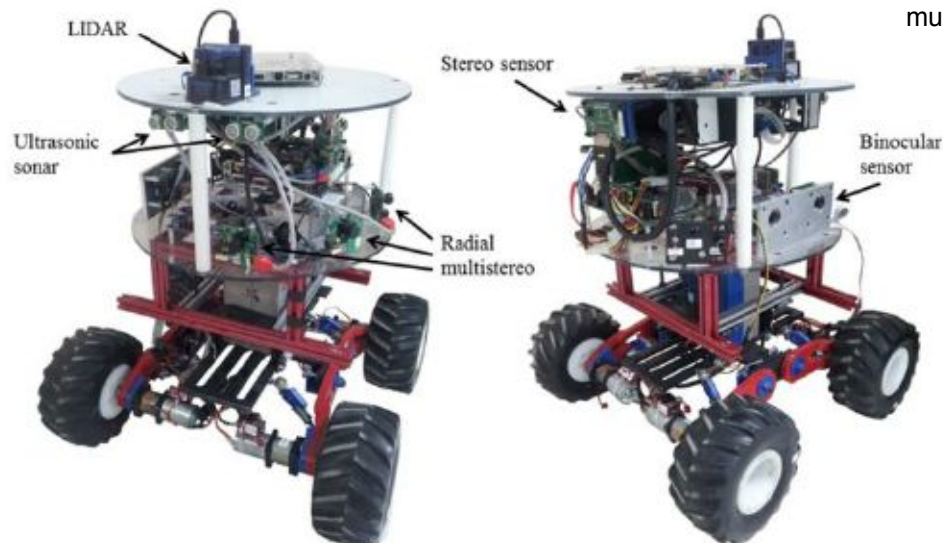
Rotary shaft/wheel encoder



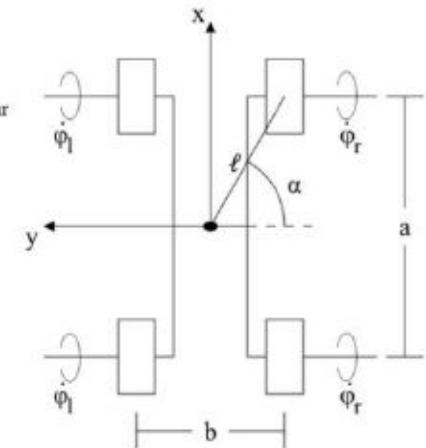
Examples of Sensor Suites



c/o Australian Centre for Robotics



from Rivero-Juarez et al "3D Heterogeneous multi-sensor global registration" 2013



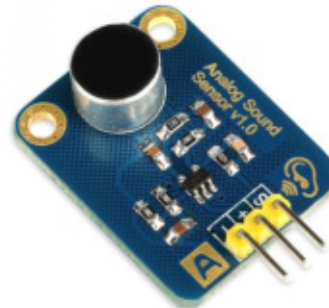
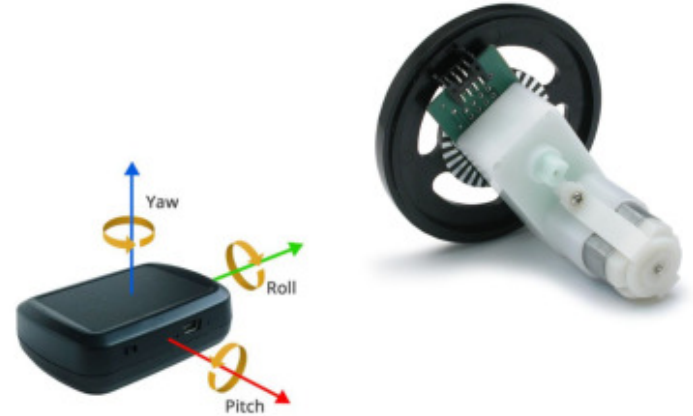
Types of Sensors: Proprioceptive vs Exteroceptive

Proprioceptive: about internal states

- Balance, acceleration
- Joint angles, wheel turns
- Humans: hunger Robots: battery level

Exteroceptive: about external states

- Light, colour
- Temperature
- Magnetic, electric fields
- Sound
- SONAR, RADAR, LiDAR
- Chemical, gas
- Humidity
- Touch, force, pressure



Types of Sensors: Analog vs Digital

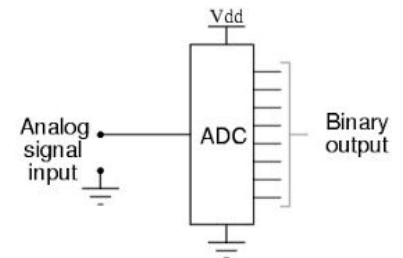
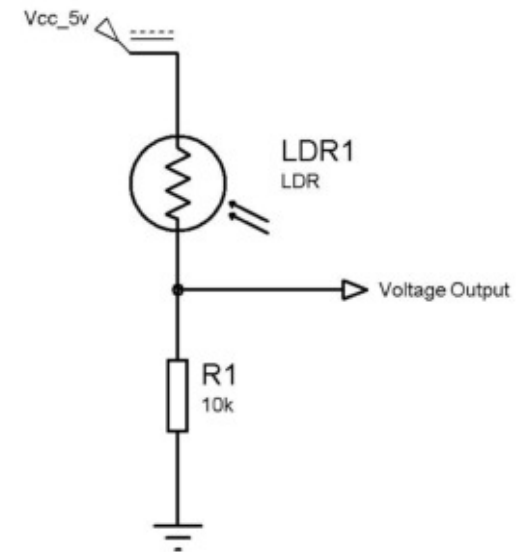
At the core of all sensors is a *transducer* that transforms one physical phenomenon (temperature, pressure, light, sound) into another (resistance, capacitance, inductance)

A circuit then typically converts this into an analog *voltage*, e.g. via a terminating resistor

For digital systems, an analog-to-digital converter then converts to a digital signal

Some microcontrollers come with built-in analog-to-digital converters

Q: is a push-button switch an analog or digital sensor?

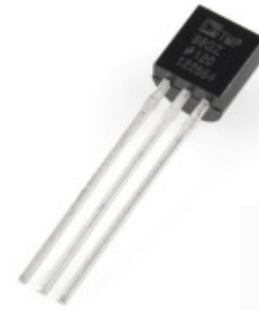


Types of Sensors: Synchronous vs Asynchronous

From the point of view of the system:

Synchronous capture

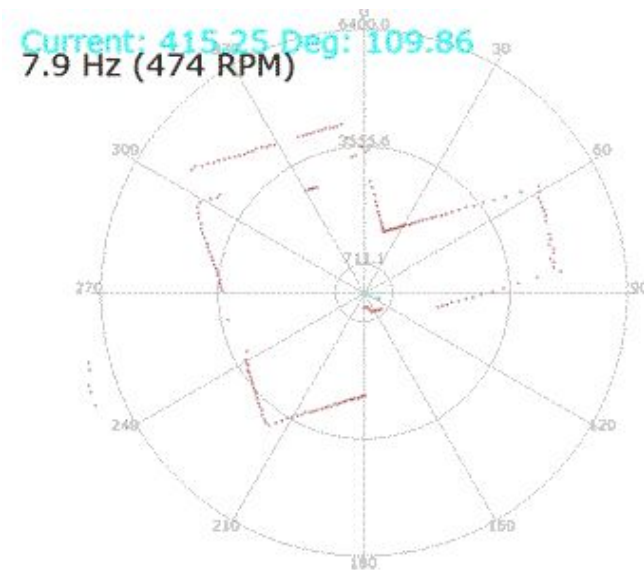
- Sensor is queried on a system-mandated schedule
- e.g. A camera with trigger line taking frames on a fixed schedule, synchronised to a flash



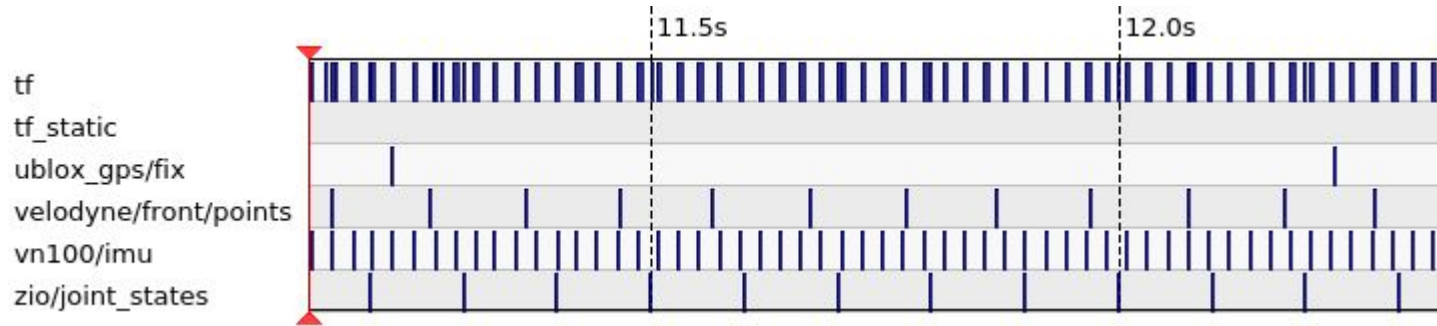
Asynchronous capture

- Sensor takes measurements on its own schedule
- Measurement timing can fluctuate, isn't easily synchronised to other sensors
- e.g. Spinning LiDAR, free-running camera

Reporting can also be synchronous or asynchronous.
e.g. a camera with a trigger that captures synchronously, but sends imagery via an asynchronous network connection



Asynchronous Capture



Asynchronous sensing is common

Design for event-driven processing

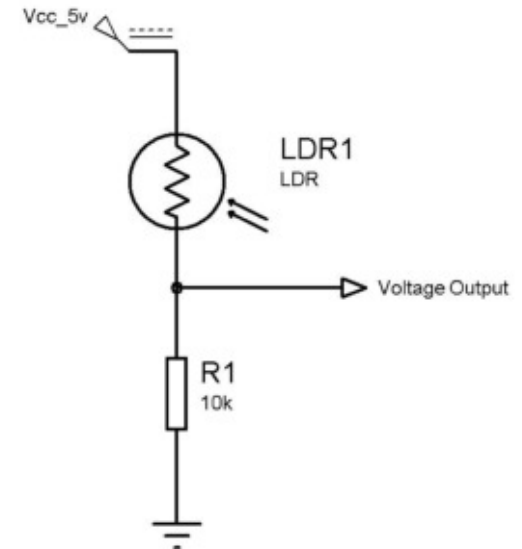
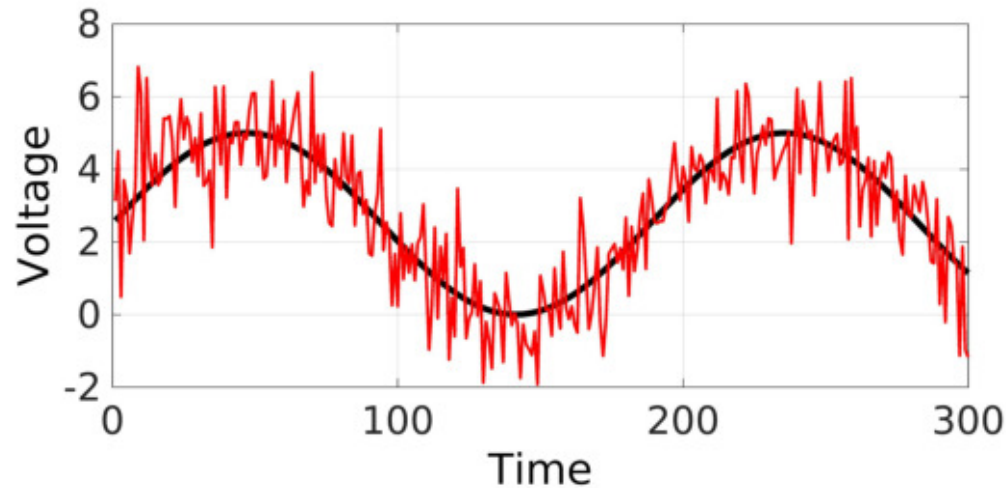
- Don't sit busy-waiting for one sensor to respond
- Process sensor reports as they arrive
- Don't assume sensors are temporally aligned

Account for variable timing

- e.g. calculating velocity from an irregularly spaced series of position measurements
- Timestamps are critical!

Non-Idealities: A Simple Experiment

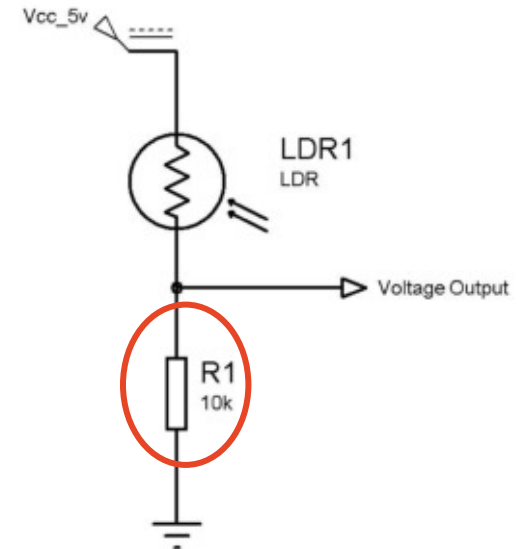
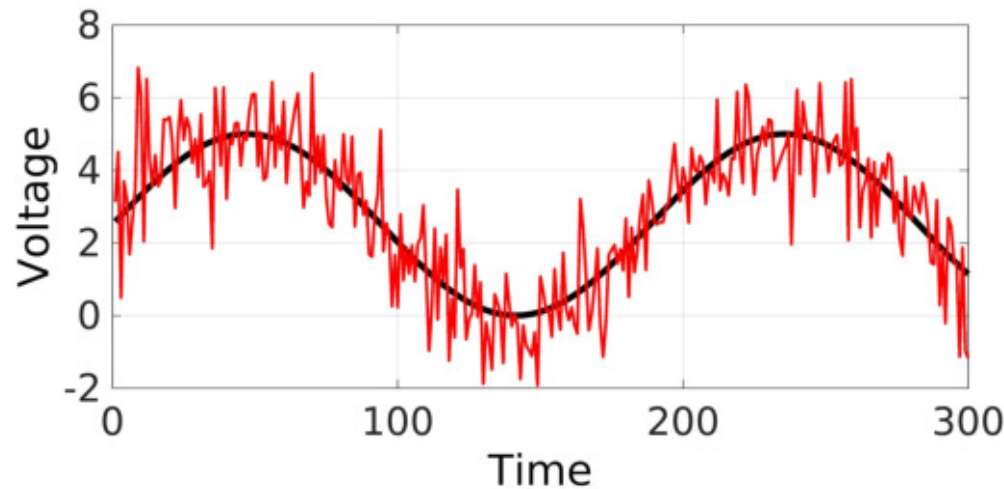
- I built this circuit in my office...
- and measured the output on an oscilloscope.
- With nothing moving in the scene, what do you expect I measured?



- What's causing the oscillation?
- Hint: it's at 100Hz (in my Australian office)
- What's causing the noise?

Non-Idealities: Thermal Noise

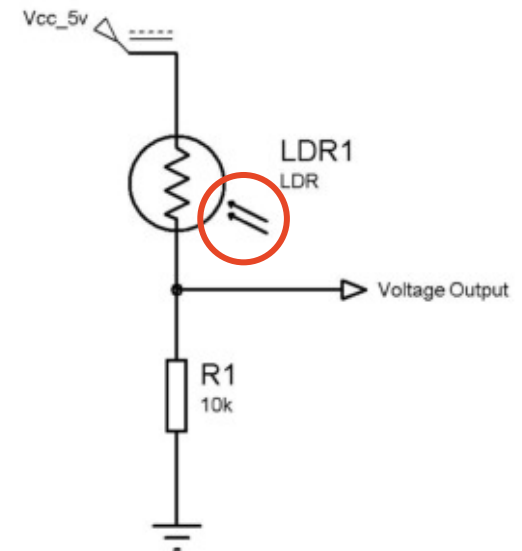
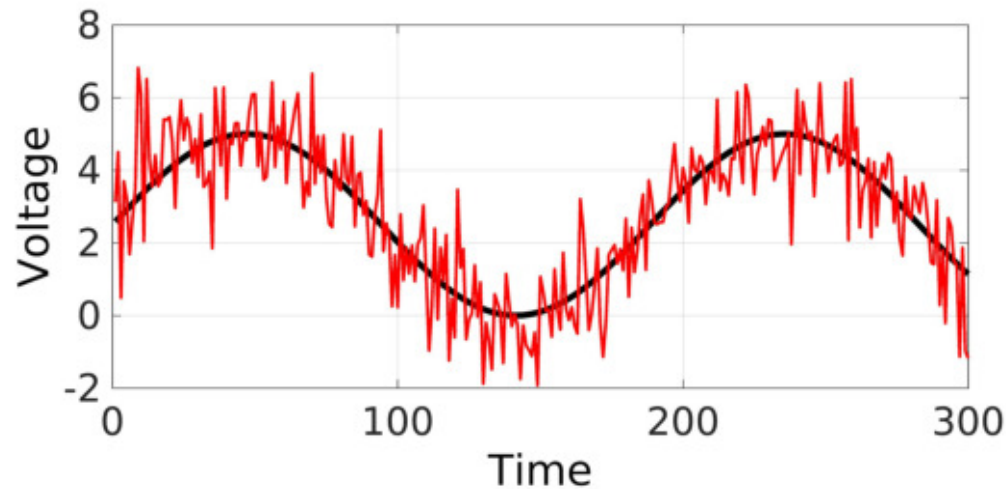
- Random thermal motion of charge carriers *inside the sensor and its analog circuitry*



- Present in all electronic components above absolute zero
- Terminating resistors are a major and unavoidable source
- Generally modelled as additive, white, and Gaussian
 - White: Equal power at all frequencies
 - Gaussian: Amplitude follows a Gaussian distribution

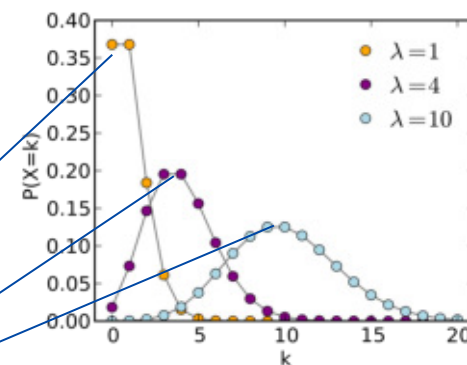
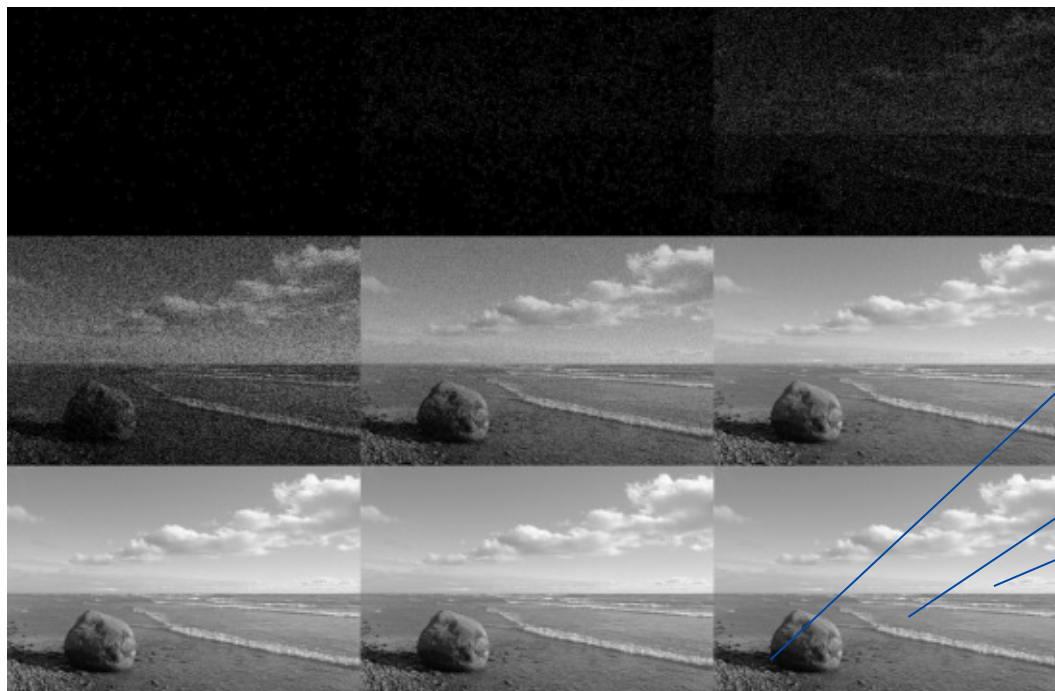
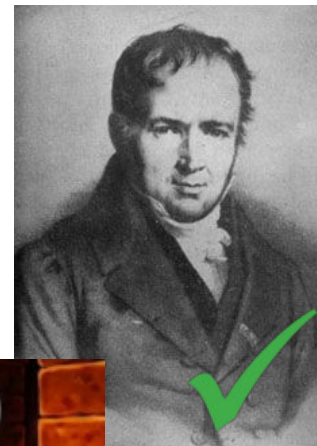
Non-Idealities: Noise *in the Scene* ?

- Random fluctuation in every *counted, random* event
- Poisson-distributed



Poisson Noise

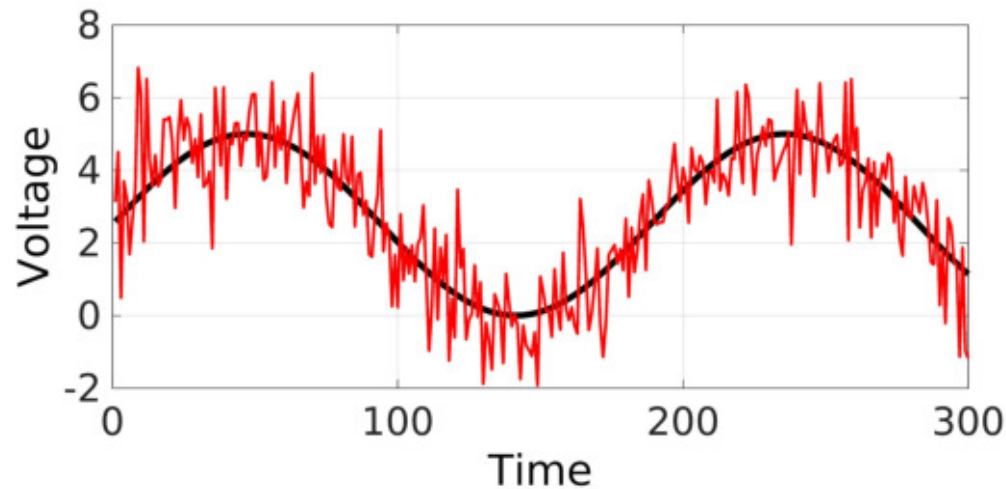
- ...or when sensing light “Photon noise”
- Characteristic of the signal, not the sensor
- e.g. lightning strikes in a year, photons arriving at a sensor
- Variance = mean; stronger signal = *more* variance!



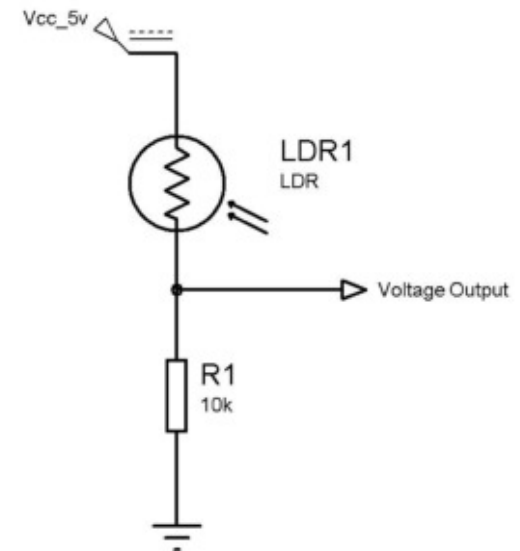
[<https://commons.wikimedia.org/wiki/File:Photon-noise.jpg>]

Non-Idealities: Model Error

- My assumptions about the world were wrong

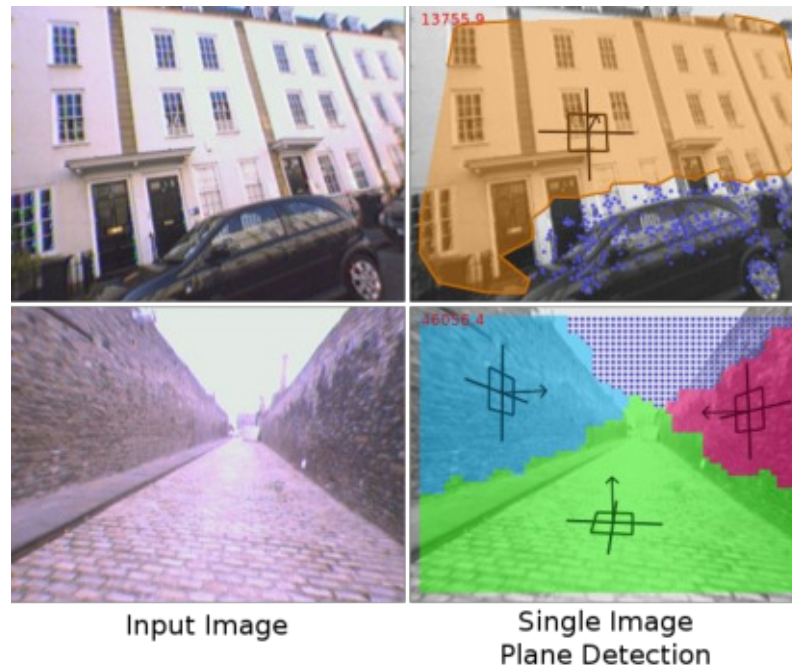


- My office has fluorescent lights
- These fluctuate with the power supply, 50Hz
- The fluctuation is with power not voltage, thus 100Hz
- Could be considered model error or interference



Model Error

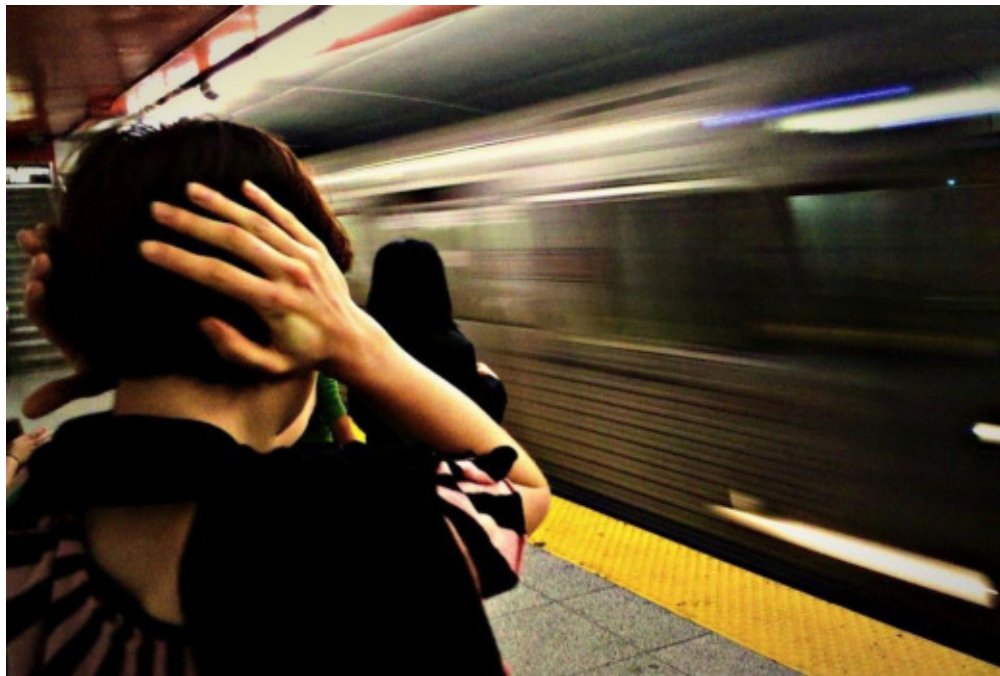
- Simplification of reality to make system design tractable
- e.g. assuming flat terrain and zero-slip wheels when performing dead reckoning with wheel counts
- Colloquially sometimes called “noise”. It’s not, it’s a real difference between reality and our approximations of reality!



[Haines & Calway 2015 "Recognising planes in a single image"]

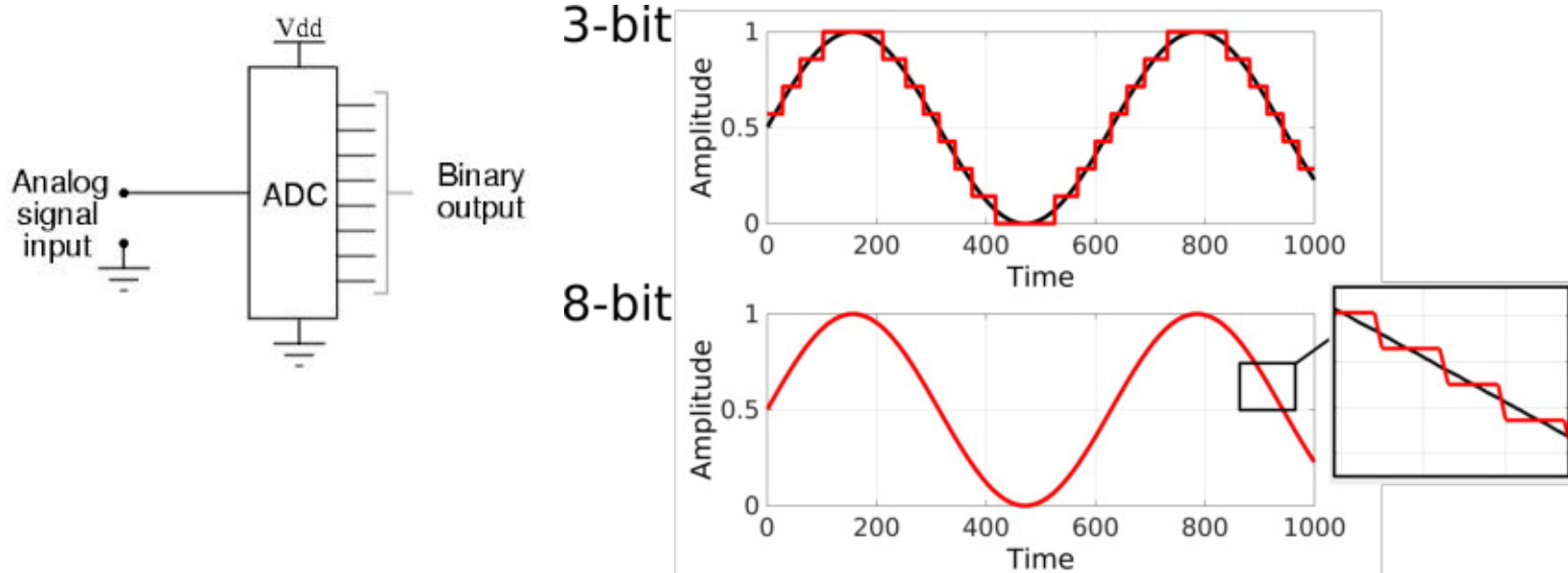
Interference

- An unwanted signal coupling onto a sensor
- Can come from the outside world (strong radio, light, sound sources)...
- ... or inside the robot (active sensors interfering with each other, unwanted electrical coupling between components)
- Colloquially sometimes called “noise”. It’s not, it’s a real signal!



Non-Idealities: Quantization

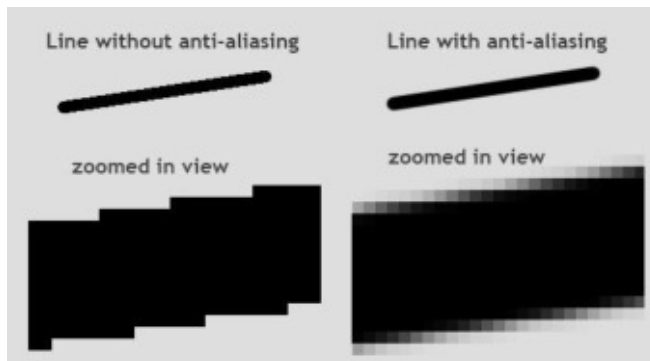
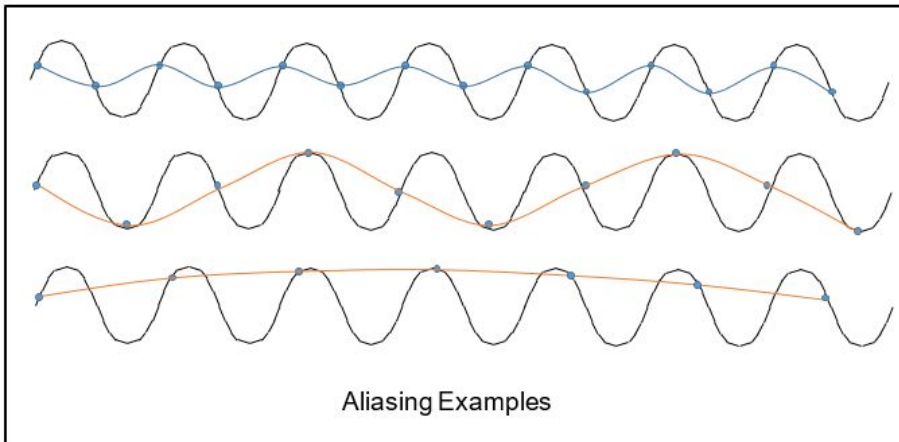
- Introduced at analog-to-digital conversion
- Digital signals approximate continuous signals with a fixed set of levels
- More bit-depth = less quantization error



An ideal analog sine wave (black) sampled by 4-bit and 8-bit ADCs (red)

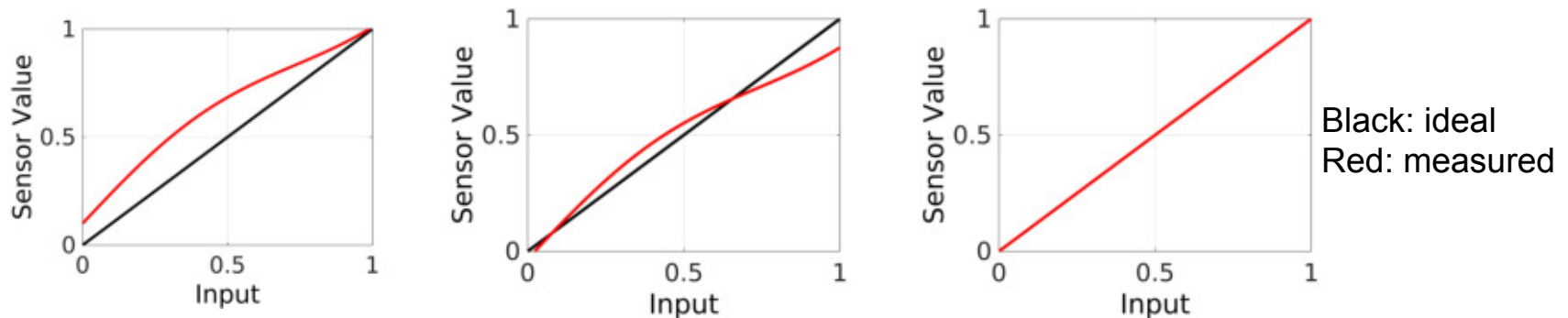
Non-Idealities: (Frequency) Aliasing

- When a signal at one frequency appears as though it were at another
- Comes from sampling a signal at discrete moments
- Often best dealt with by anti-aliasing filters *at capture time*
 - Average measurements over a window - lowpass filter
- It's predictable so can be useful
 - Measure high frequency events with low-frequency sensor



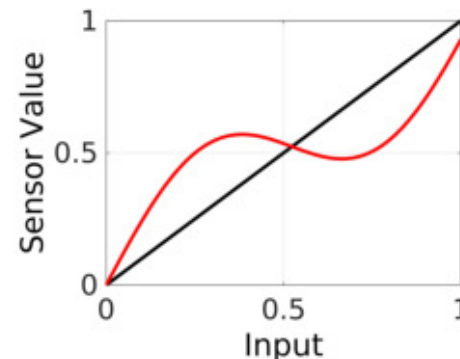
Non-Idealities: Non-linearity, scaling, and bias

- Bias: additive offset from ideal
- Scaling: multiplicative offset from ideal
- Non-linearity: warped / deviated with respect to ideal
- These non-idealities can sometimes be reduced or eliminated through “*intrinsic*” calibration, measuring the sensor’s *internal* behaviour



A sensor with no calibration, bias removal, and ideal calibration

Q: Could this sensor be perfectly corrected through calibration?



Aleatoric vs Epistemic Uncertainty

Aleatoric

Due to random, unpredictable events

e.g. thermal noise, Poisson noise

From “alea”, dice

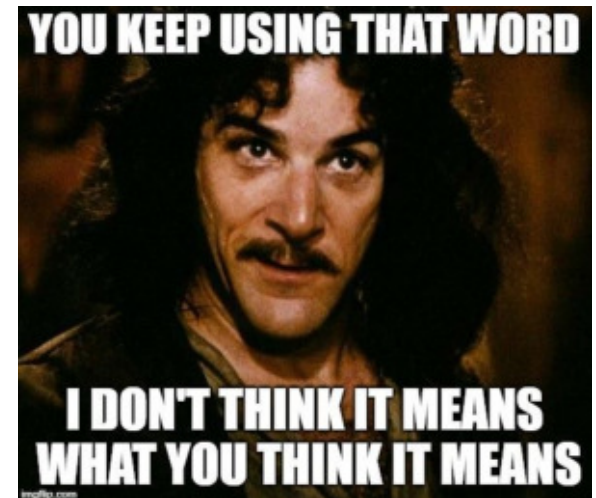


Epistemic

Due to incomplete knowledge about the world

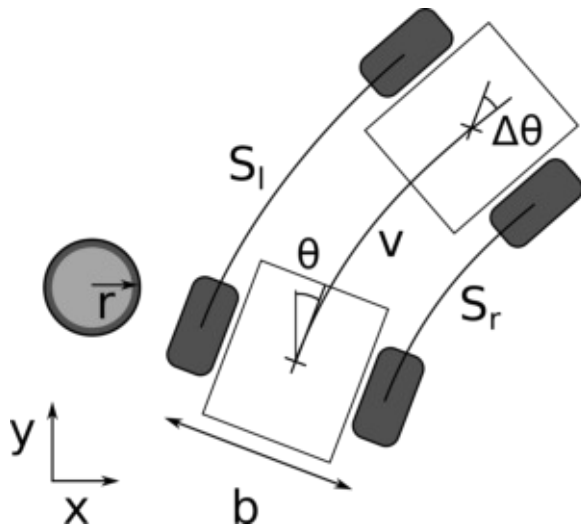
e.g. model error, calibration error

from Greek “epistēmē”, knowledge

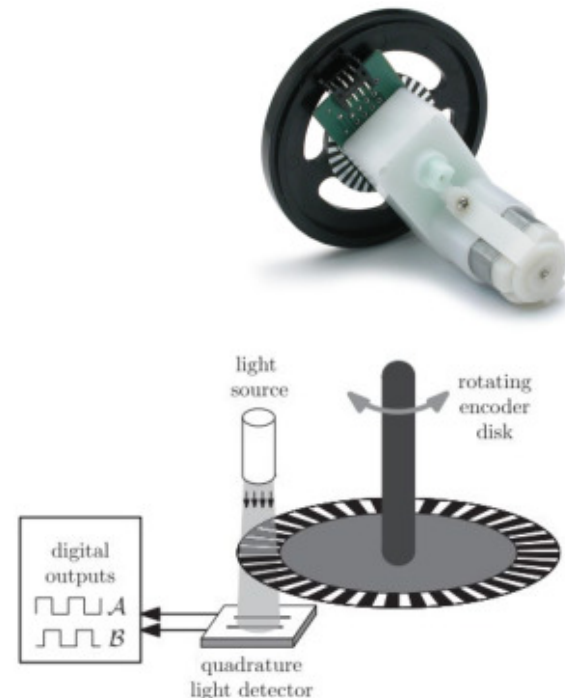


Example: Odometry From Wheel Encoders

- Dead reckoning (sometimes “deduced” or “ded” reckoning, it’s debated whether this is the original sense)
- Counting wheel turns tells you how far you’ve driven
- Differencing left and right wheels tells you how you’ve turned
- Lots to know about using this well



$$\begin{aligned}v &\approx 2\pi r(S_l + S_r)/2 \\ \Delta\theta &\approx 2\pi r(S_l - S_r)/b \\ \Delta x &\approx v \sin(\theta) \\ \Delta y &\approx v \cos(\theta)\end{aligned}$$

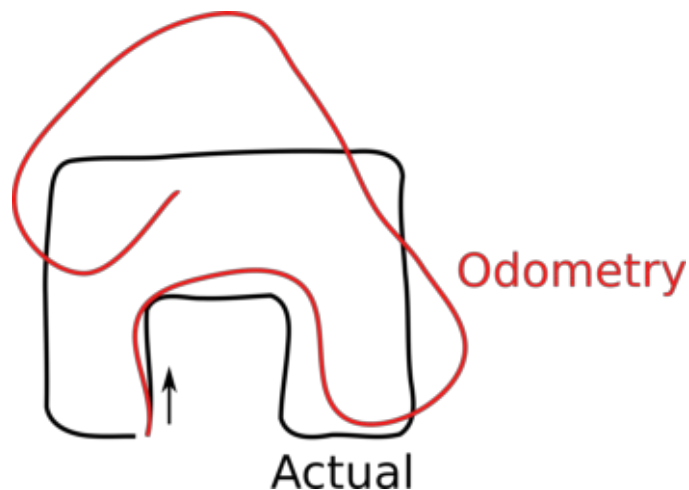


<https://bharat-robotics.github.io/blog/dc-motor-speed-control/>

Example: Odometry From Wheel Encoders

Problem: Over long periods, odometry error grows, why?

- *Sensor noise? (Thermal? Poisson? Quantisation?)*
- Miscalibration: baseline, wheel size
- Model error: Wheel slippage, irregular terrain, wheel compression
- Interference: wind, unruly students
- Small angular errors result in large position error over time
- Error accumulates without bound



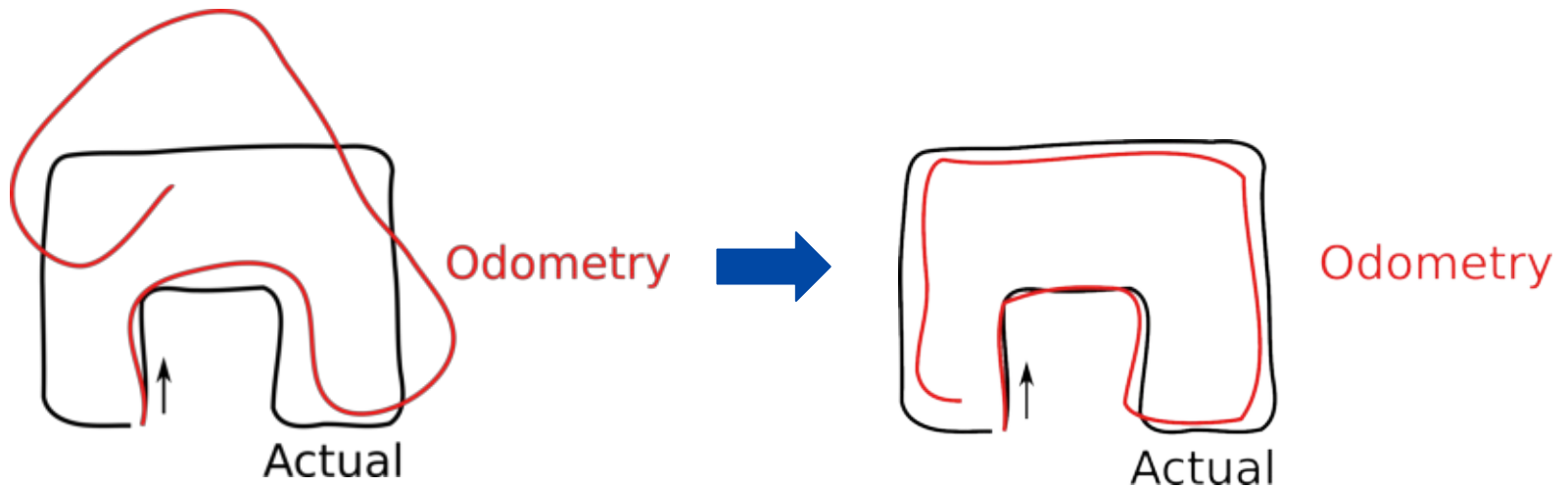
Complementary Sensors and Sensor Fusion

Take the most useful characteristics of each sensor and combine them in a joint solution

- Complementary filter (*think “smart averaging”*)
- Kalman filter (*think “fancy averaging that knows about noise/uncertainty”*)
- Generally requires relative pose between sensors, “*extrinsic*” calibration

A very simple example:

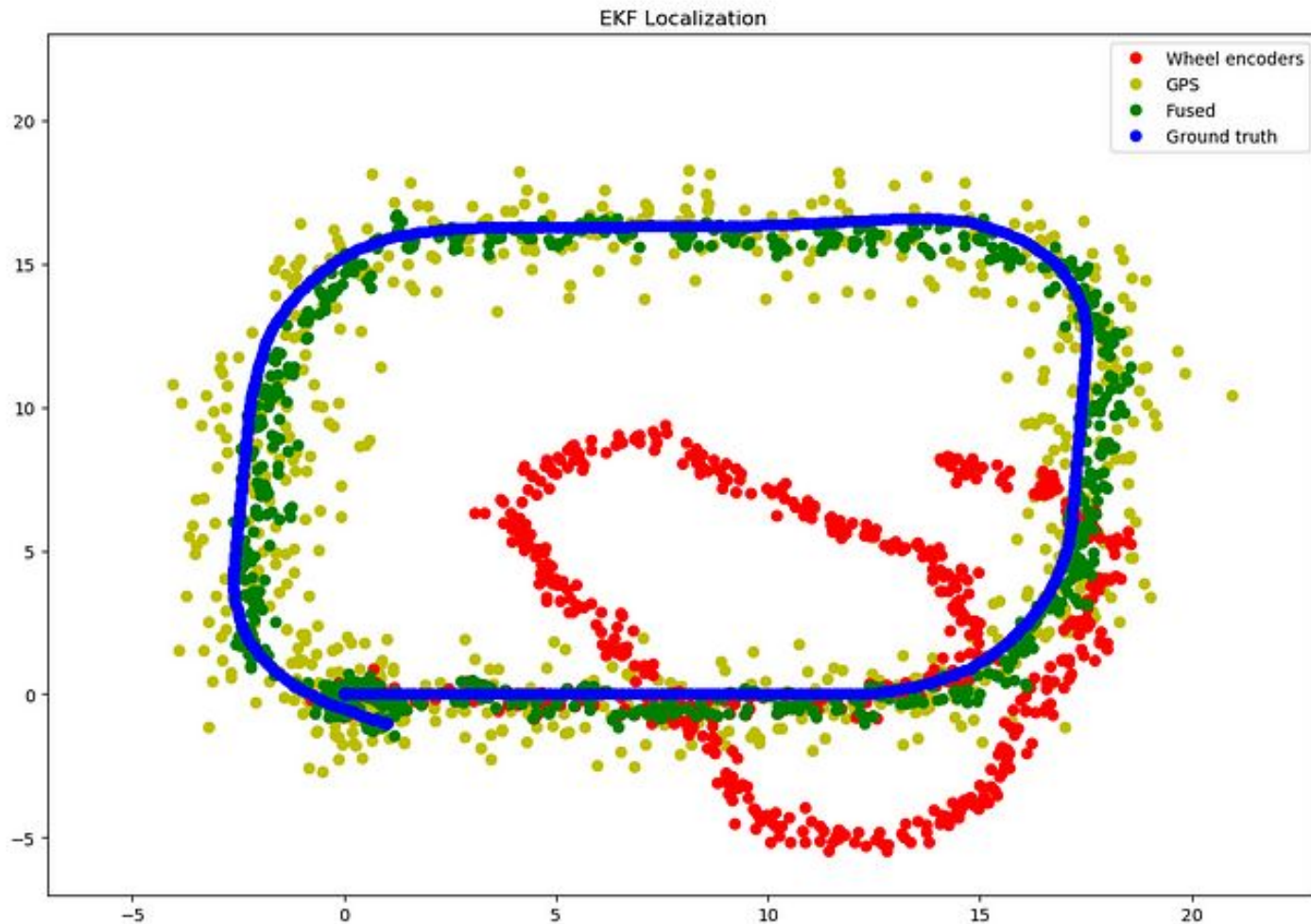
- Wheel turns for distance travelled - locally pretty good
- Compass for direction - direction error doesn't accumulate



Example Complementary Sensors

GPS: short-term noisy, long-term stable

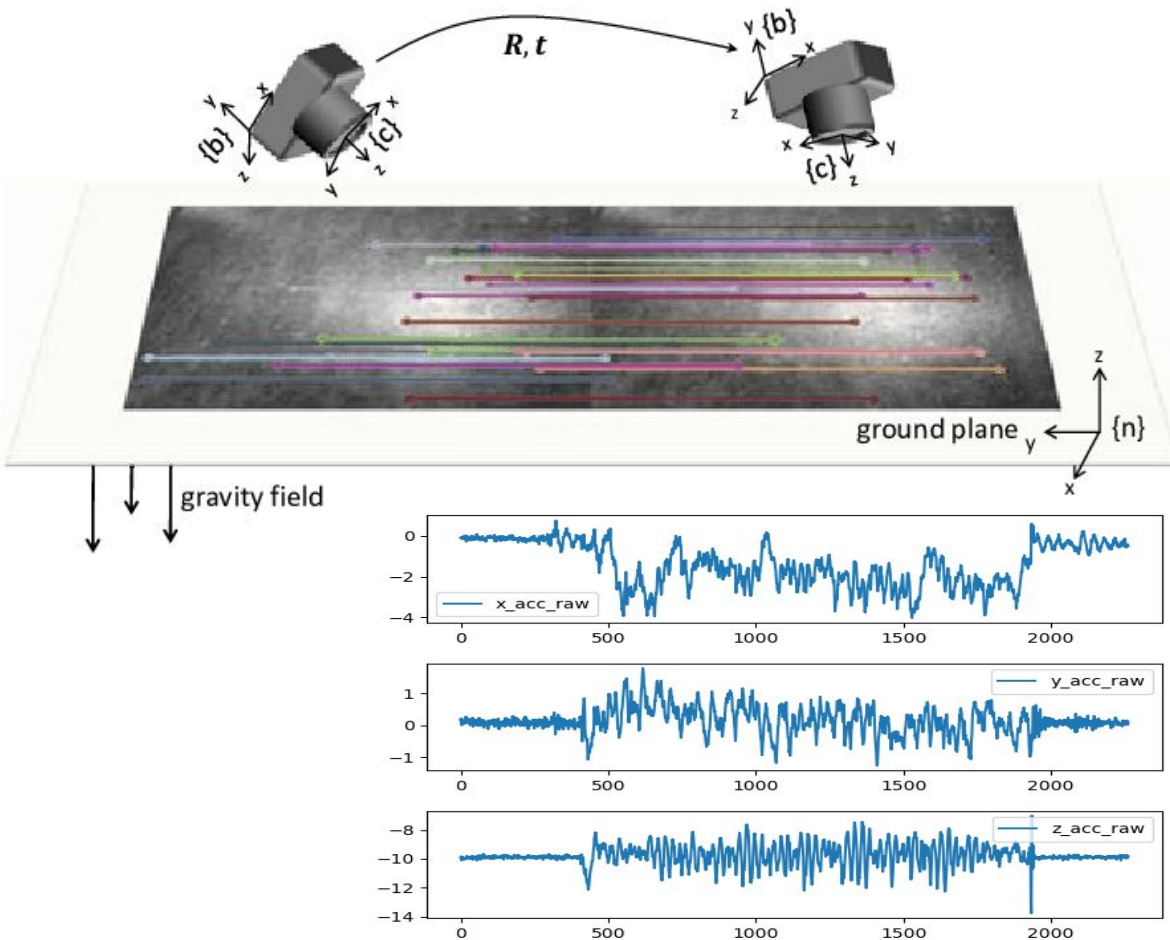
Wheel odometry: short-term accurate, long-term accumulates error



Example Complementary Sensors

Camera: low frequency, no drift

IMU: very high frequency, some stable (compass / gravity), some drift



Example Complementary Sensors

LiDAR: colour-blind, depth

Camera: “depth-blind”, colour

RGB image



3D point cloud



7D colored point cloud

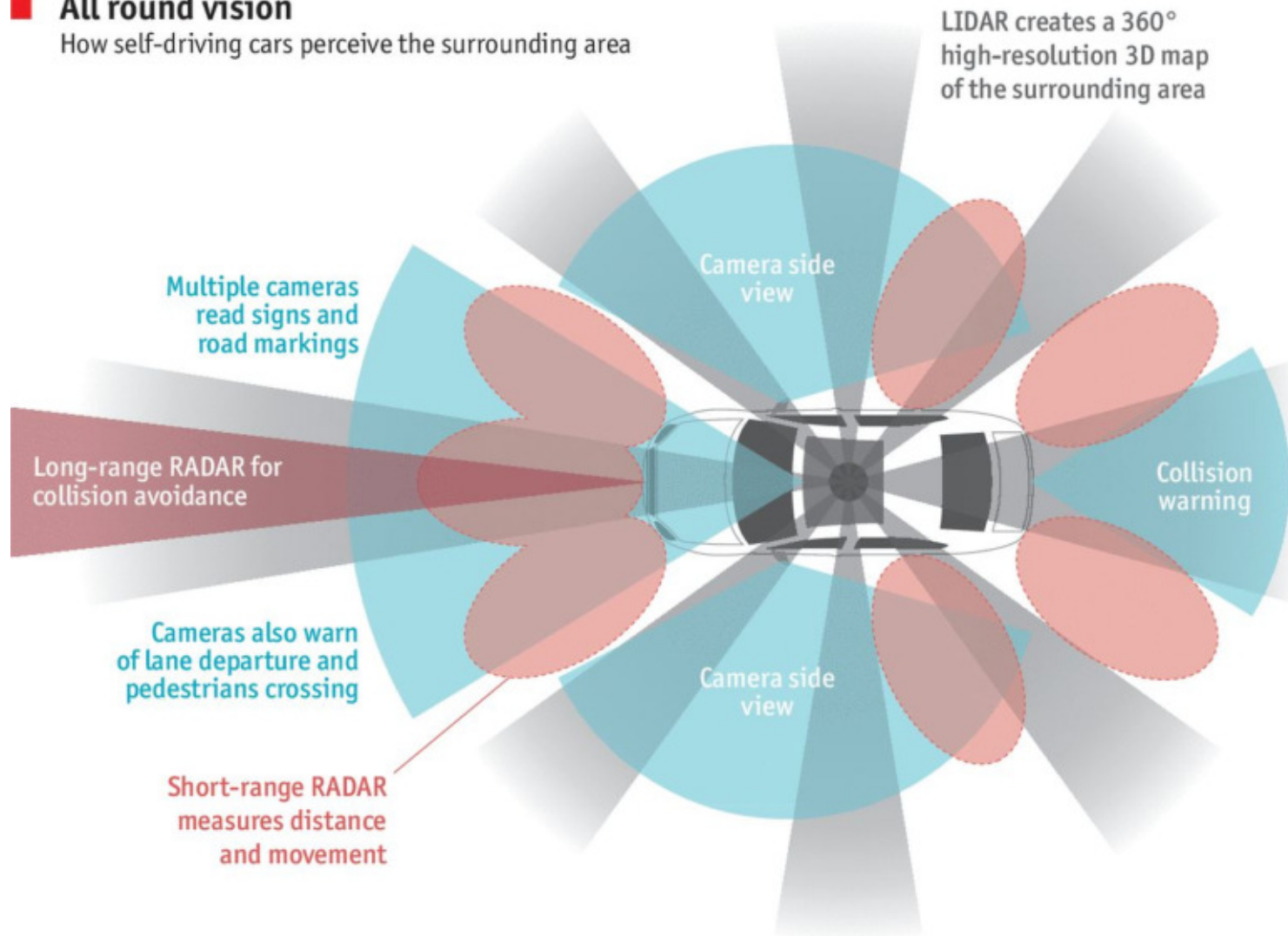


[wang2023]

Example Complementary Sensors

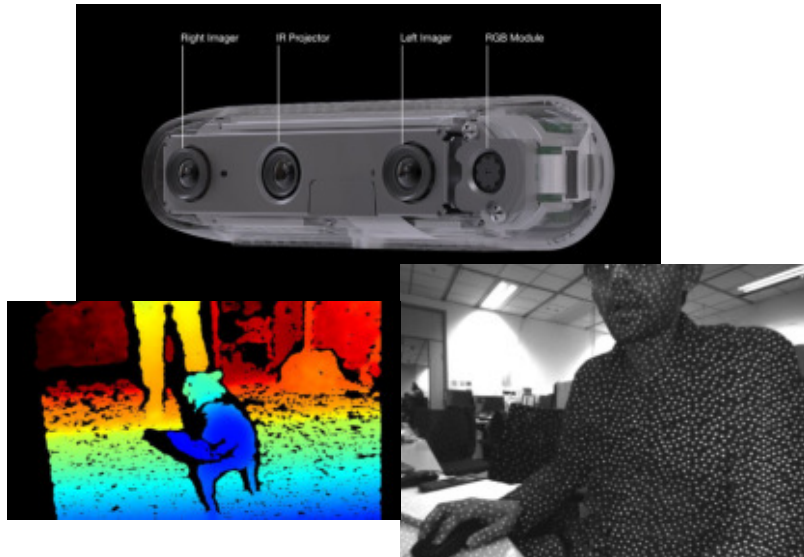
All round vision

How self-driving cars perceive the surrounding area

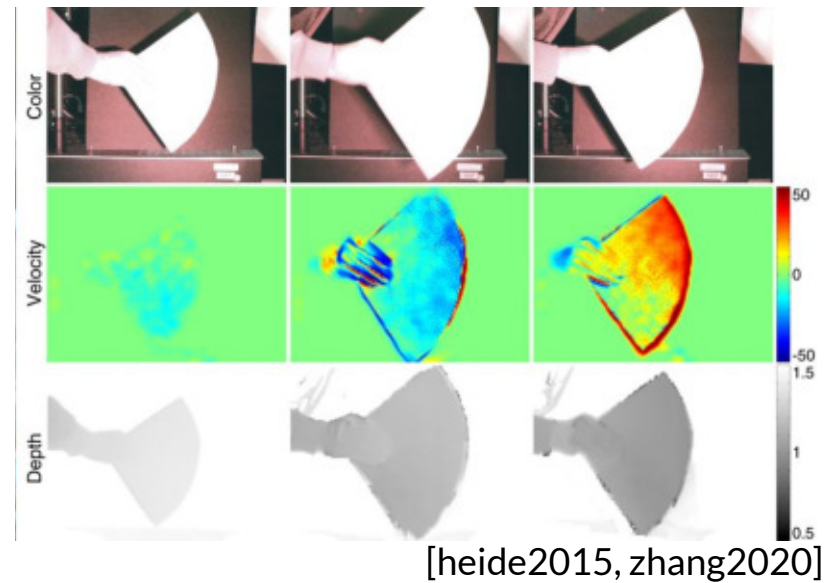


Modern and Emerging Sensors

[Active] Stereo



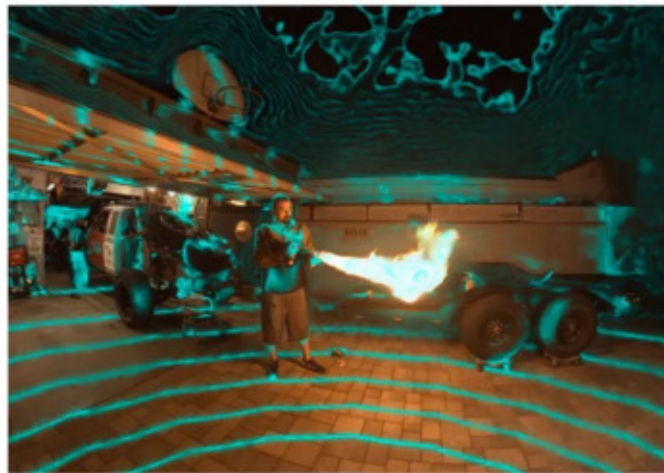
[Doppler] Time of Flight



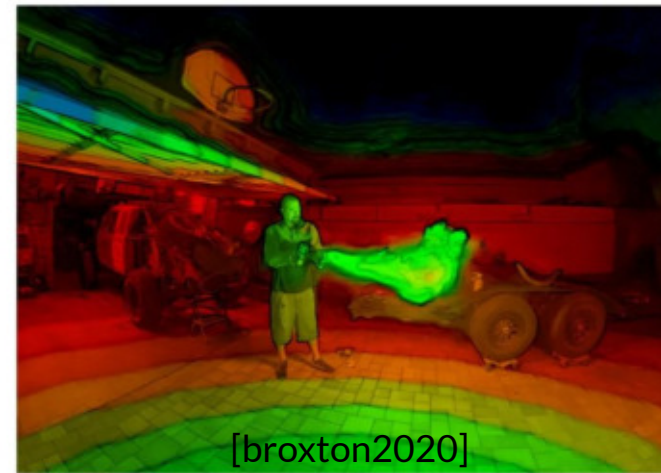
Light Field



(a) Capture Rig



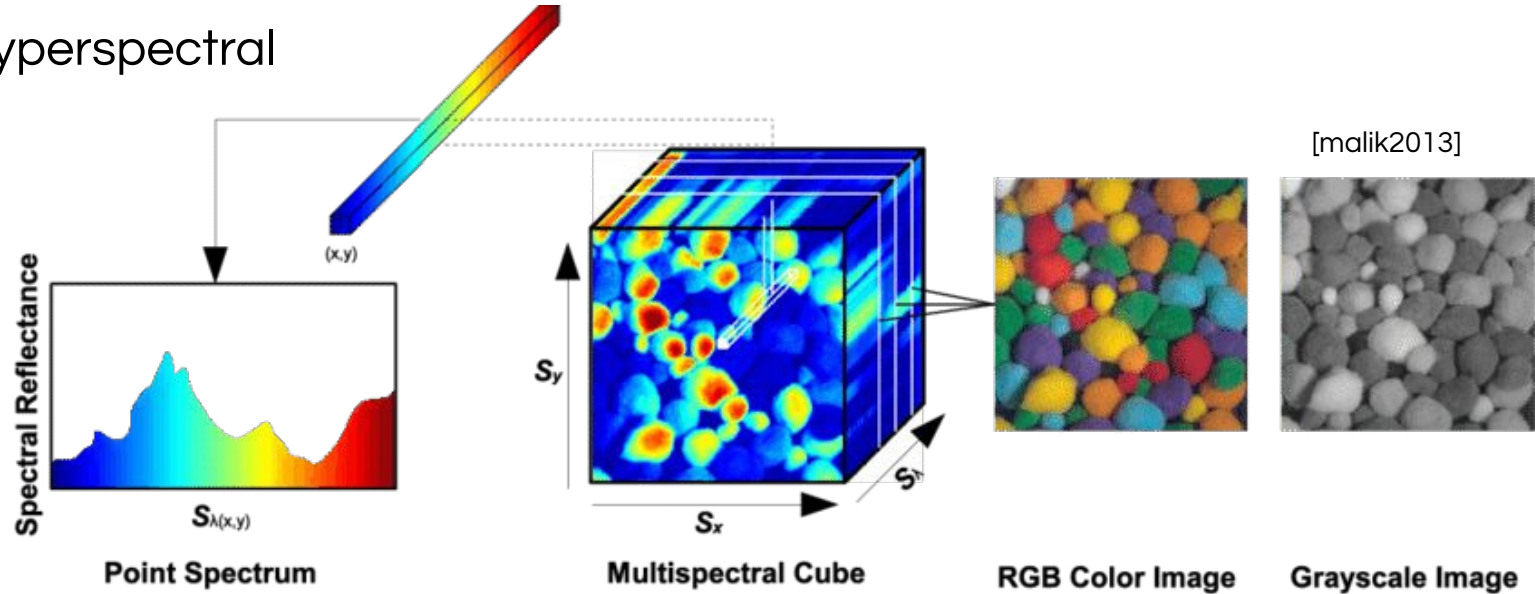
(b) Multi-Sphere Image



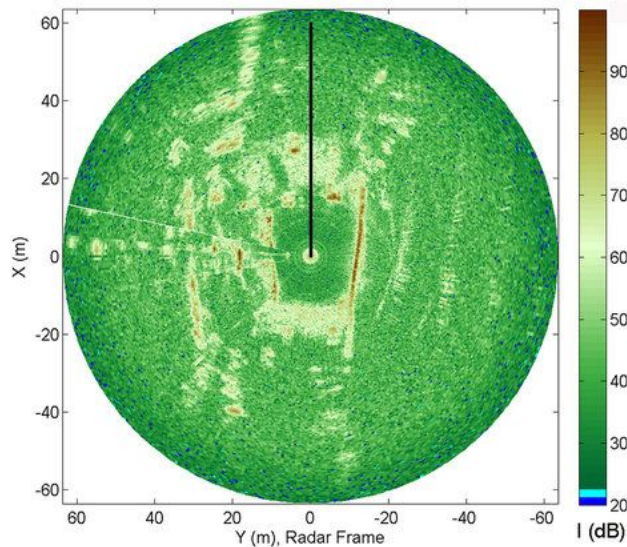
(c) Layered Mesh Representation

Modern and Emerging Sensors

Hyperspectral

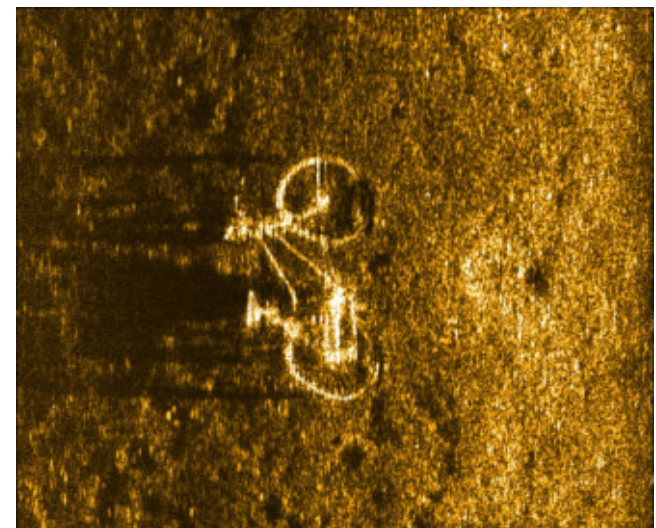


Radar



[reina2015]

Sonar



Discarded Womens Bike

Sensors

Kinds of Sensors:

- Proprioceptive, Exteroceptive

- Active vs. Passive

- Analog, Digital

- Synchronous, Asynchronous

Non-Idealities:

- Model error, thermal noise, poisson noise

- Quantisation, aliasing, interference

- Non-linearity, scaling, bias

- Calibration

- Aleatoric vs epistemic uncertainty

Example: Odometry From Wheel Encoders

Complementary Sensors and Sensor Fusion

Example Complementary Sensors

Modern and Emerging Sensors