Sensors

Luís Paulo Reis

lpreis@fe.up.pt
Director/Researcher LIACC
Associate Professor at FEUP/DEI

Armando Sousa
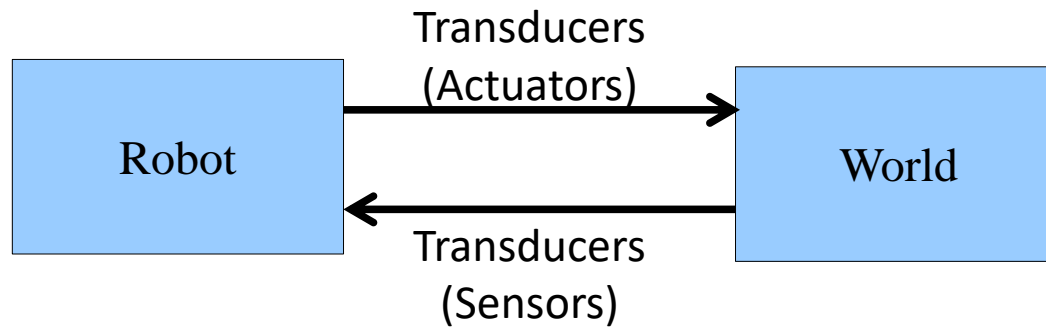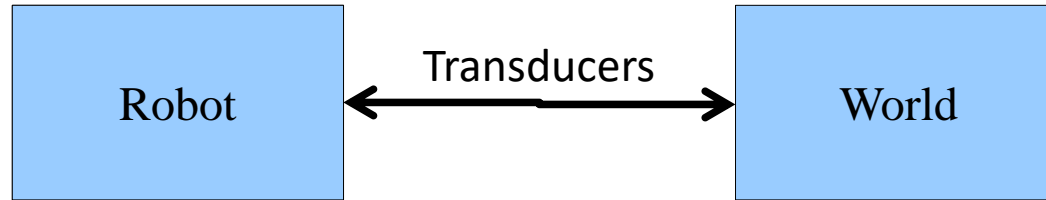
asousa@fe.up.pt
Researcher INESC-TEC
Assistant Professor at FEUP/DEEC

*Also, a very special Thank You to: **Prof. Nuno Lau, IEETA, U. Aveiro***

Robot & World

The Perception Problem

The Perception Problem

- **What does a robot needs to sense**
  - Depends on what the robot needs to do
  - Animals have evolved sensors that suited to their environment and position in the ecosystem

    $\Rightarrow$ A good robot designer should follow similar principles

- **Two possible questions:**
  - Given a sensory reading, what was the world like when the reading was taken?
  - Given a sensory reading, what should I do?

The Perception Problem

- **The first question**
  - Focused on world representation
  - Perception is considered in isolation

- **The second question**
  - Perception without the context of action is meaningless
  - Systemic view of the robot design
    - Task to perform
    - Best suited sensors
    - Most suited mechanical design

Some current sensing methods

- **Action oriented perception**
  - Direct link between perception and action

- **Expectation-based perception**
  - Sensor interpretation constraining based on world knowledge

- **Task-driven attention**
  - Direct perception where information is needed or likely to be provided (focus-of-attention)

- **Perceptual classes**
  - Partition world in manageable categories

What is a sensor?

Sensors:

- Are transducers (change physical properties)
- Map physical attribute(s) to a [quantitative] measure(s)
- Produce results, measurements over time
- Constitute the perceptual system of the robot (perception after measurement)
- Sensor "chain" (perception chain likely hardware + software)
- Transducer + electronics + ADC + software

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Human sensing

Sense	Physical attribute	Organ
Vision	EM waves	eyes
Audition	Pressure waves	Ears
Gustation	Chemical properties	Tongue
Olfaction	Chemical properties	Nose
Tact	Contact pressure/texture	Skin

- Humans can also sense other things like temperature, pain, equilibrium, own body
- Several animals have still other types of sensor capabilities

Robot sensors

- **Proximity**
  - Infrared, Sonar, laser, optical, capacitive, inductive
- **Position**
  - Potentiometer, switch, buttons, encoder
- **Heading**
  - Compass, gyroscope
- **Temperature**
  - Thermocouple
- **Sound**
  - Microphone

- **Force, Pressure**
  - Piezoelectric, variable resistance
- **Battery, Current**
  - Thermocouple
- **Chemical**
  - Several
- **Magnetic field**
  - magnetometer
- **Vision**
  - Camera
- **Etc…**

Levels of sensing

- **Attribute to be measured**
- **Physical principle of transduction**
  - Determines many of the characteristics of the sensor
- **Hardware**
  - Electronics
- **Software**
  - Signal processing
  - Computation
  - Sensor fusion

Levels of sensing

- **Attribute to be measured**

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- **Software**
  - Signal processing

  - Computation

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Sensor Characteristics

- Field of view and Range
- Accuracy, repeatability and resolution
- Responsiveness in the target domain
- Power consumption
- Hardware reliability
- Size
- Computational complexity
- Interpretation reliability

Accuracy…

True Value · Average Of Meas. · Precision · Accuracy · Resolution
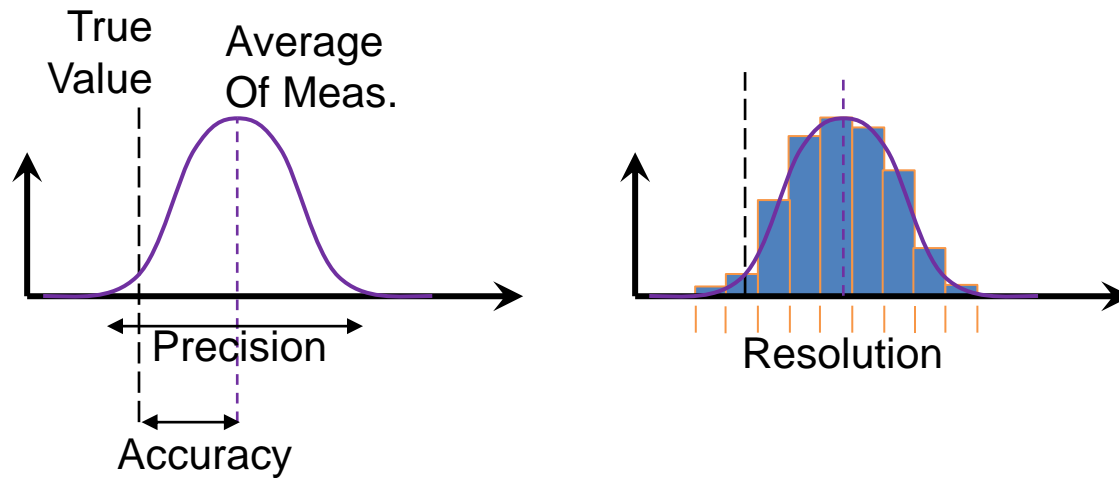
High Accuracy AND High Repeatability · Low Accuracy BUT High Repeatability · Medium Accuracy AND Medium Repeatability · Low Accuracy AND Low Repeatability

https://www.pi-usa.us/en/tech-blog/the-difference-between-position-accuracy-and-repeatability-and-methods-to-reduce-position-errors/

Optional viewing: *https://www.youtube.com/watch?v=-Lit-lusMZk*

Sensor errors

- **Systematic errors**
  - Always push the measured value in the same direction
  - Can be reduced by sensor calibration
  - Ex: temperature in sonar, wheel radius in odometry
  - Note: Interference is different, some interferences can be measured and corrected by sensor fusion like techniques

- **Non systematic errors**
  - Have a more random behavior
  - Cannot be predicted or eliminated by calibration

≠ Interference (external influence)

Classification of sensors

- **Passive sensors**
  - Rely on environment to provide the medium for observation
  - Ex: Camera, thermocouple, microphone
  - Less energy
  - Reduced Signal to Noise ratio
- **Active sensors**
  - Emits form of energy and measures the impact
  - Ex: sonars. X-ray
  - Restricted enviroments

Classification of sensors

- **Proprioceptive**
  - Measure values internally to the system
  - Ex: motor speed, battery status, joint angle, etc.

- **Exteroceptive**
  - Information from the robots external environment
  - Generally considering the robots frame of reference
  - Depend on something external

Proprioceptive sensors

- Potentiometers
- Encoders
- Inertial navigation system
- Compass
- Gyroscopes
- Battery sensors

Potentiometer

- **Physical principle:**

  Linear tension variation at the output of a variable resistance

- **Can be used to detect angular or linear position**
  - Joint angle, servomotor, etc
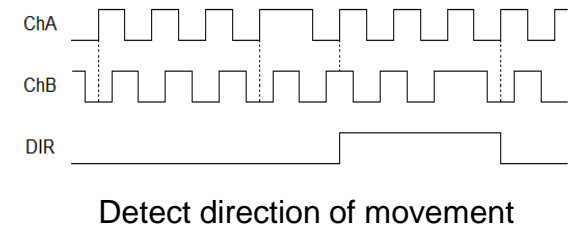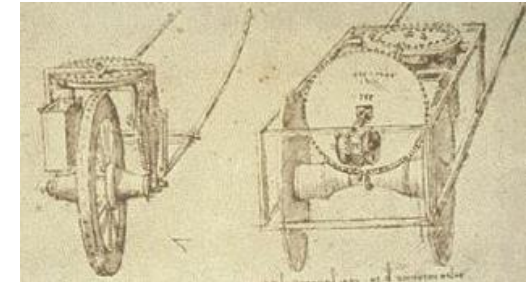

19
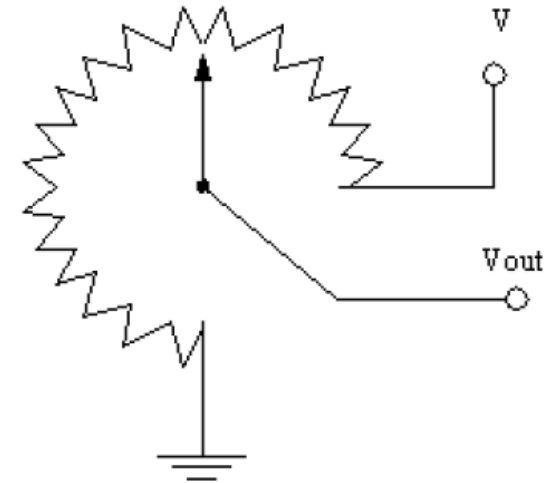
Encoders / Odometry

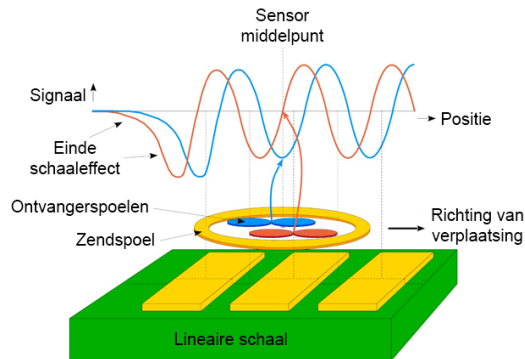- **Physical principle**
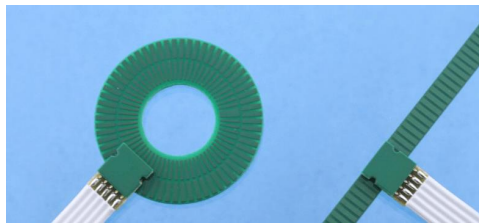
  Record the wheel traversed distance

- **Wheel traversed distance is used to estimate robot position and orientation**

$$v = \frac{v_1 + v_2}{2}$$

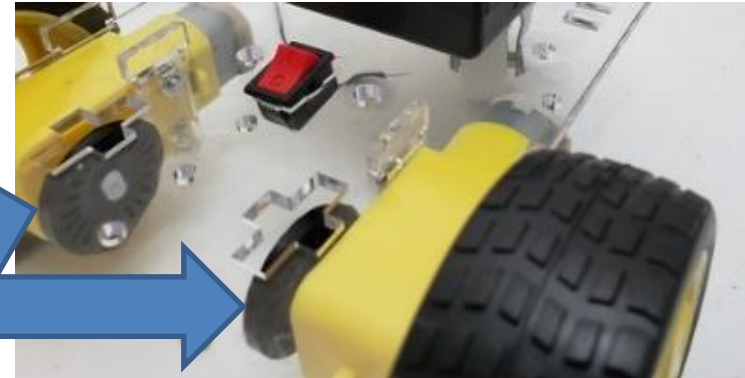$$\omega = \frac{v_1 - v_2}{b}$$

Detect direction of movement

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Encoders / Odometry

Magnetic version
of an encoder:
(Rotary or linear)

The two encoder wheels,
one for each motor,
beneath transparent
floor of the robot

https://automaticaddison.com/
how-to-make-an-autonomous-wheeled-robot-using-ros/

Sensor middelpunt

Signaal

Einde schaaleffect

Ontvangerspoelen

Zendspoel

Positie

Richting van verplaatsing

Lineaire schaal

https://e.sentech.nl/en/news/
inductive-encoder-accurately-measure-
displacement-in-harsh-conditions

https://hackaday.io/project/
158496-imcoders/log/147068-robot-odometry

GPS/DGPS

- **Physical principle**

  Triangulation over the distance to several satellites

- **Estimates longitude, latitude and altitude**

  - Resolution: 10-15m

- **DGPS (Differential GPS)**

  - Extra GPS receivers at known locations are used to reduce errors
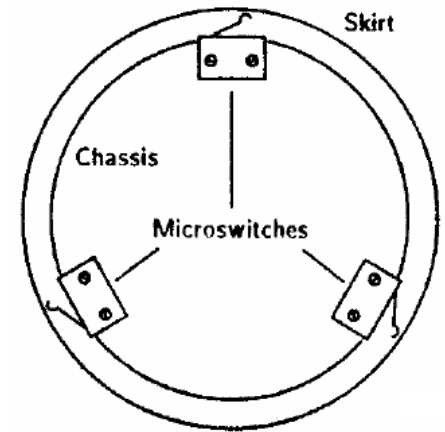
  - Resolution: few centimeters

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Proximity sensors

- **Bumper**

- **Infrared**

- **Sonar**

- **Laser Range Finder**

Bumper

- **Physical principle**

  Direct contact closes (or opens) a circuit

- **Used to detect collisions**

- **Binary value**

- **Reliable but the collision is eminent**

Infrared sensor

- **Physical principle**

  Na IR emitter/receiver is used
  to detect distance or as a barrier

- **Used to estimate distance ,
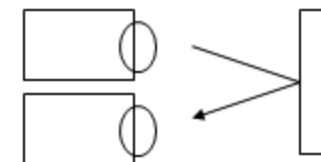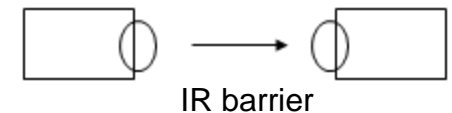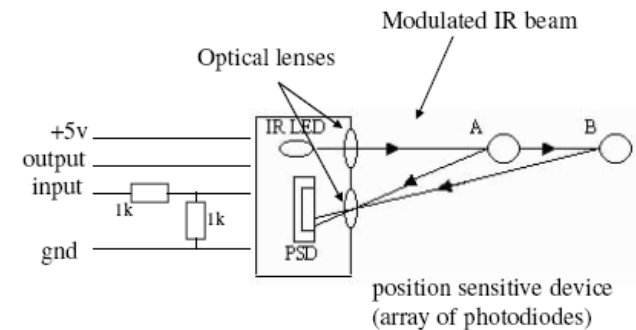 presence of objects or color**
  - Some dark surfaces do not reflect IR

- **Several technologies**

- **Range: from <10cm to ~1m**

- **Narrow field of view**

- **Cheap**

Modulated IR beam

Optical lenses

position sensitive device
(array of photodiodes)

IR barrier

Sonar

- **Physical principle**

  Emit US chirp, time until echo is received is used
   to estimate distance

- **Time until echo is proportional to the distance until cl** **obstacle**

  – Speed of sound changes with temperature and pressure

- **Range: few centimeters to ~10m**

- **Field of view ~30º**

- **Cheap (but not as cheap as IR)**

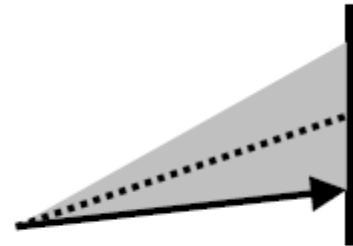- **Fast (depends on range)**

- **Ring of sonars**
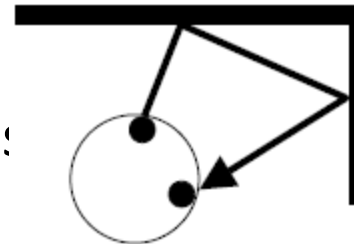
Sonar problems

- **Foreshortening**

- **Crosstalk**
  - Receiver may detect echoes f range returned s in the ring

- **Specular reflection**
  - Wave is reflected when angle is

Laser range finder

- **Physical principle**

  Similar to sonar but uses laser instead of sound

- **Time of flight is used to estimate distance**

- **Range: 2m until ~500m**

- **Resolution: 1 cm**

- **Field of view: 100º-180º**

- **Much more accurate than sonar**

- **Also more expensive**
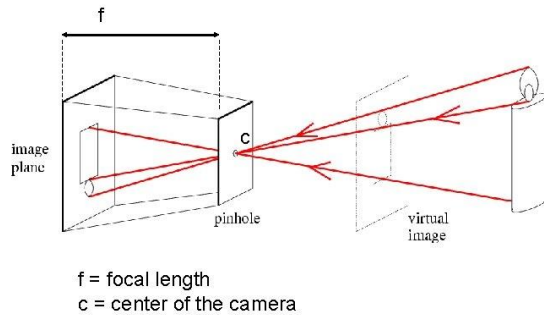

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Vision

Pinhole camera

f = focal length
c = center of the camera

Figure from Forsyth

https://slidetodoc.com/pinhole-camera-model-computational-photography-derek-hoiem-university/

A/B=A'/B'

A=P.y

B'=Znear   B=P.z

© www.scratchapixel.com

https://www.scratchapixel.com/lessons/3d-basic-rendering/3d-viewing-pinhole-camera/how-pinhole-camera-works-part-2

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Depth Sensing

Wenbing Zhao

Depth Sensing

https://www.terabee.com/time-of-flight-principle/
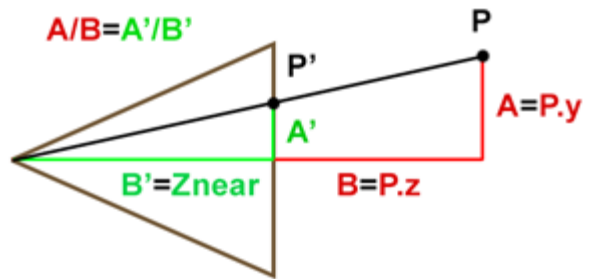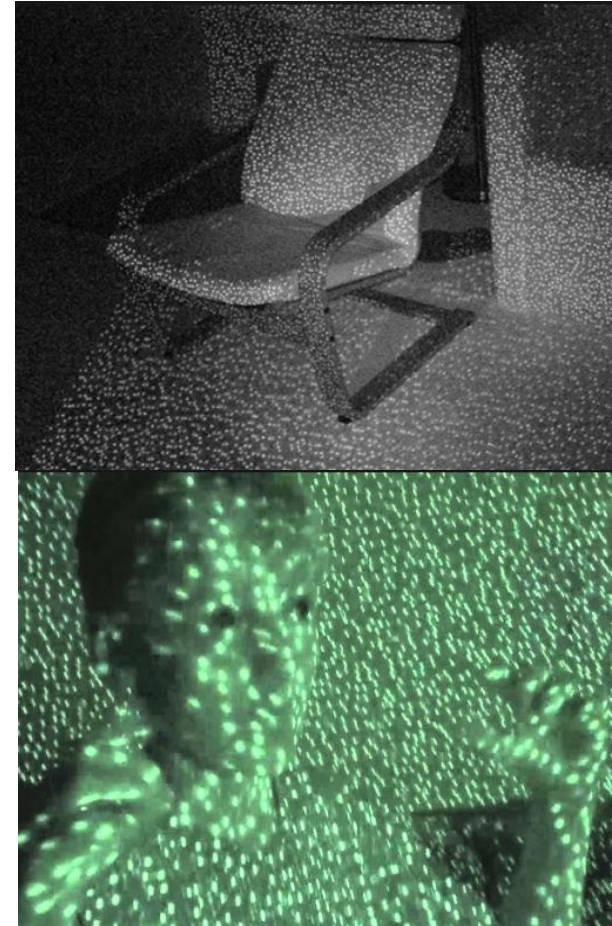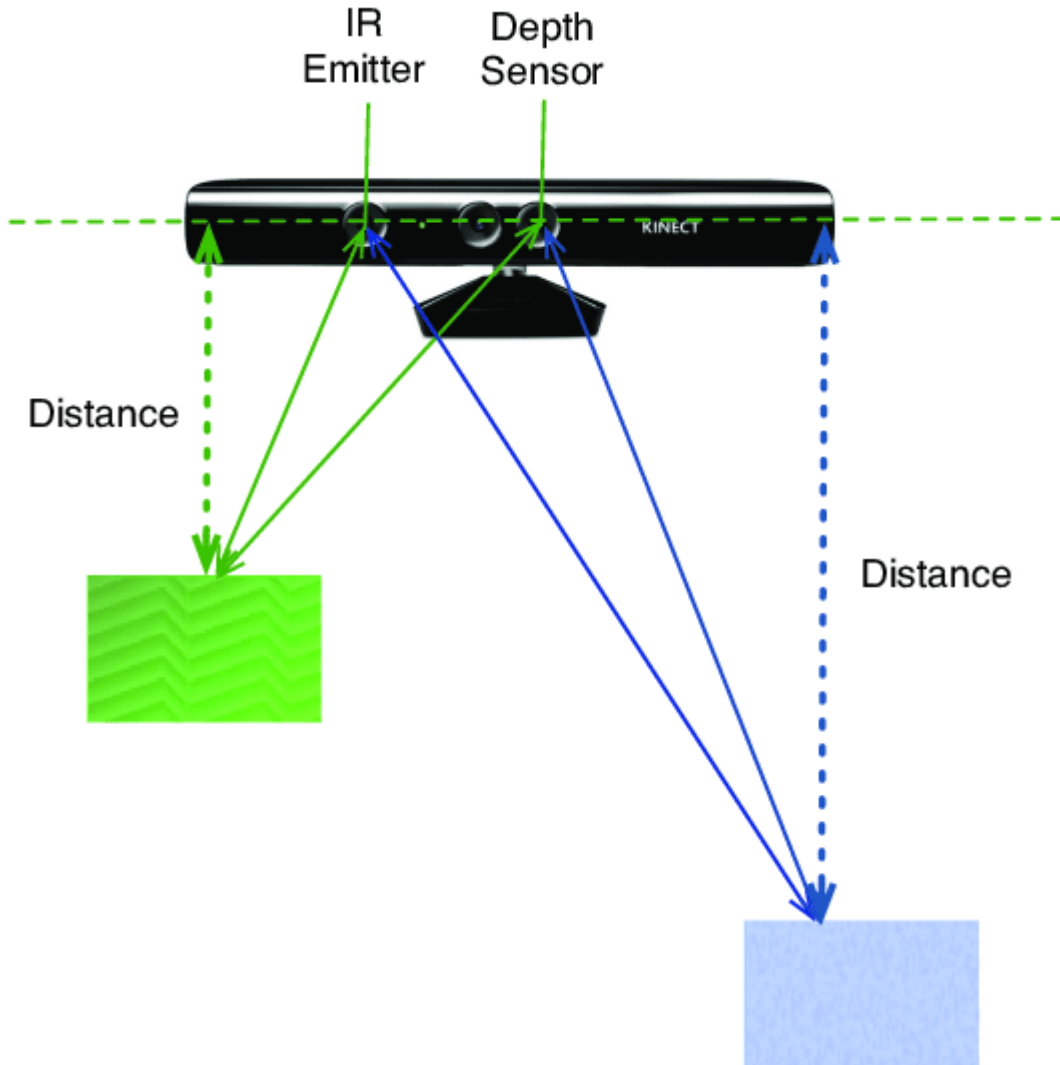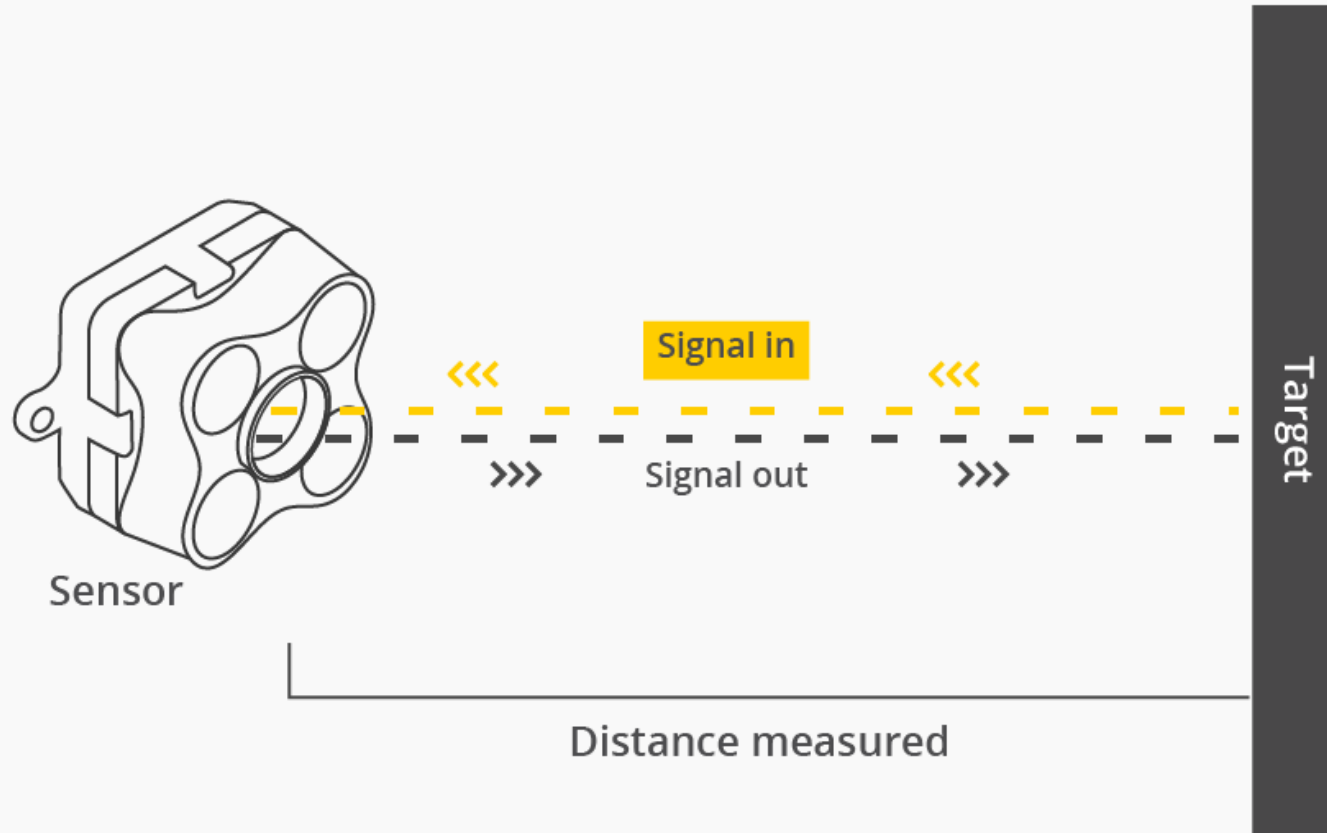
Stereo Vision
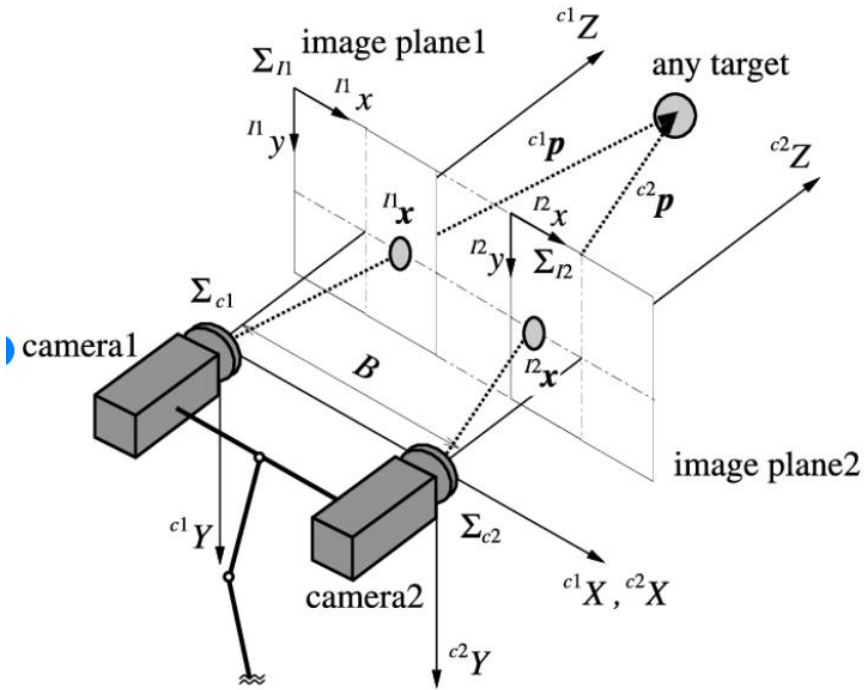
Visual tracking of unknown moving object by adaptive binocular visual servoing 1999

DOI:10.1109/MFI.1999.815998

- IEEE Xplore
- Conference: Multisensor Fusion and Integration for Intelligent Systems, 1999

https://www.stereolabs.com/zed-2i/
https://www.stereolabs.com/solutions/robotics/

Active Stereo

https://www.osela.com/depth-sensing/
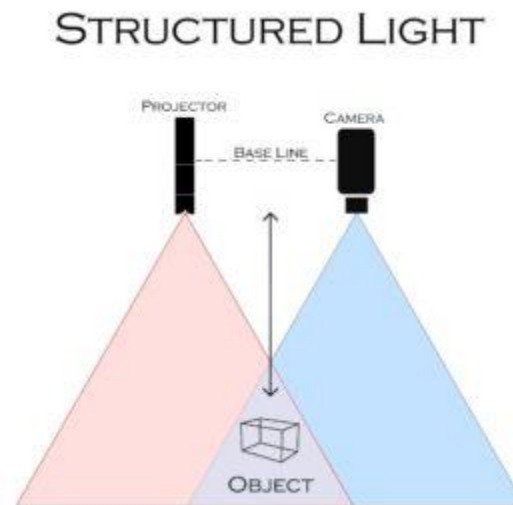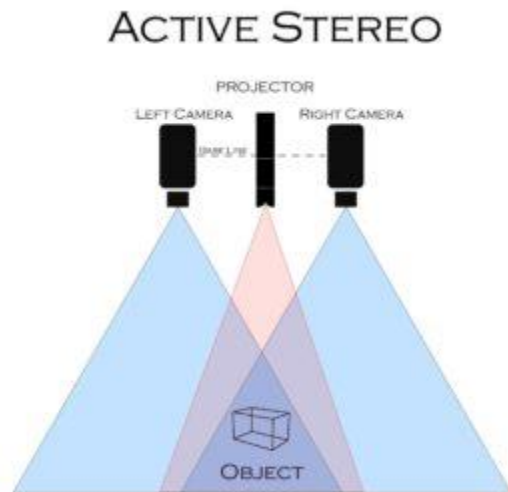
RGBD

- https://p3d.in/ifOvj   (interactive!)

RGBD – Point Cloud

(a)   (b)   (c)   (d)

https://blog.bricsys.com/point-clouds-whats-the-point/

(a) input mesh

(b) annotated edges

(c) point cloud

(d) k-nn graph

(e) extracted patches (violet)
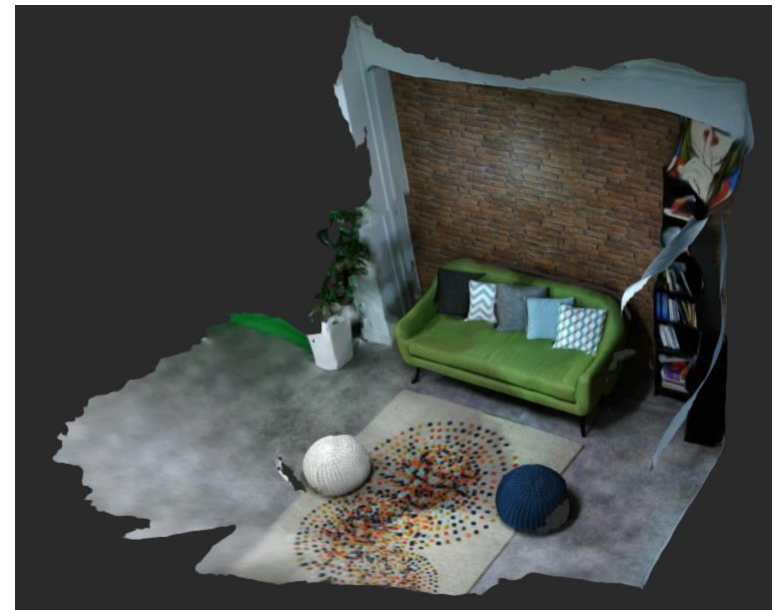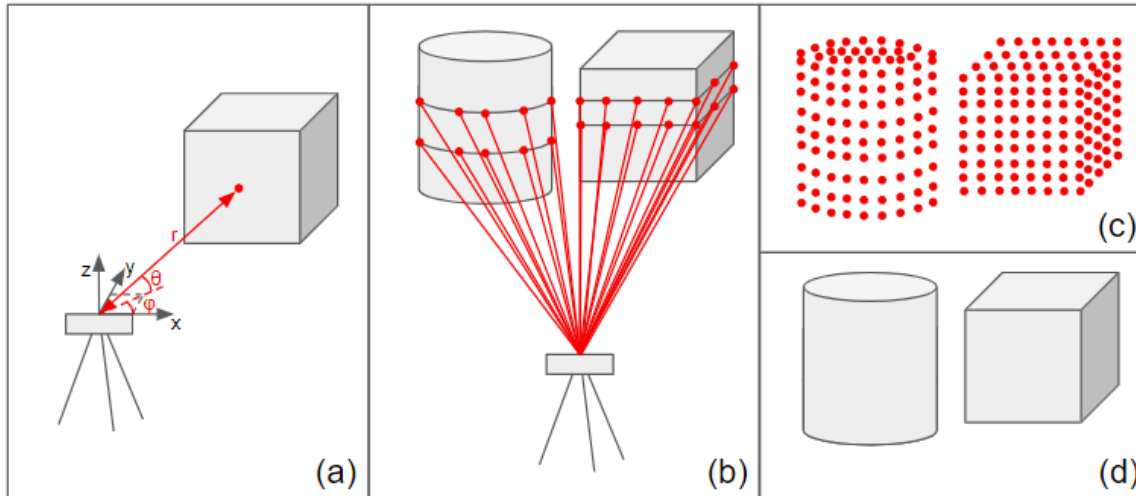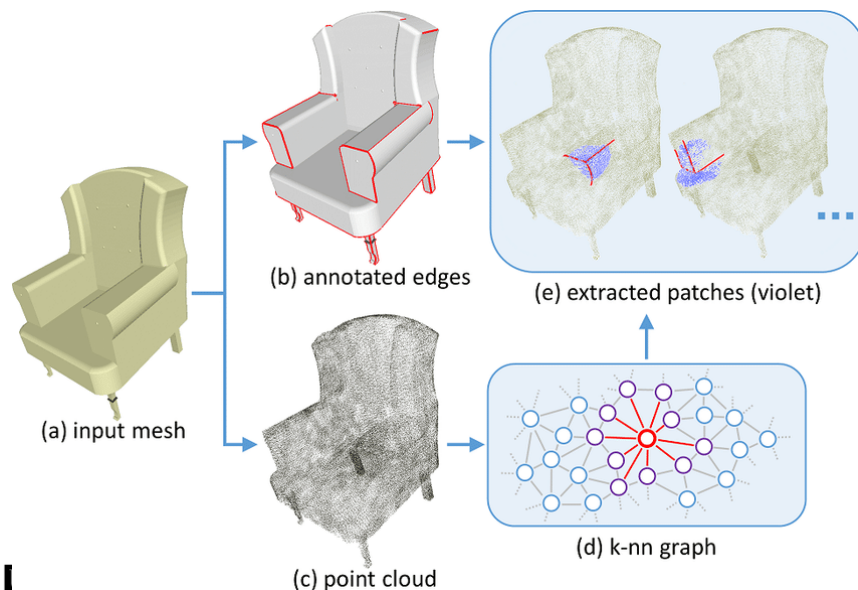
Yu, Lequan & Li, Xianzhi & Fu, Chi-Wing & Cohen-Or, Daniel & Heng, Pheng-Ann. (2018). EC-Net: an Edge-aware Point set Consolidation Network.

https://www.researchgate.net/publication/326459389_EC-Net_an_Edge-aware_Point_set_Consolidation_Network

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Automotive Sensors / LIDAR

Alpha Puck™ Velodyne Lidar®

https://www.roboticsbusinessreview.com/unmanned/unmanned-ground/velodyne-touts-latest-lidar-advances-autonomous-vehicle-partnerships/

Thrun et al.

Signals from GPS (global positioning system) satellites are combined with readings from tachometers, altimeters and gyroscopes to provide more accurate positioning than is possible with GPS alone

Lidar (light detection and ranging) sensors bounce pulses of light off the surroundings. These are analysed to identify lane markings and the edges of roads

Radar sensor

Video cameras detect traffic lights, read road signs, keep track of the position of other vehicles and look out for pedestrians and obstacles on the road

Ultrasonic sensors may be used to measure the position of objects very close to the vehicle, such as curbs and other vehicles when parking

The information from all of the sensors is analysed by a central computer that manipulates the steering, accelerator and brakes. Its software must understand the rules of the road, both formal and informal
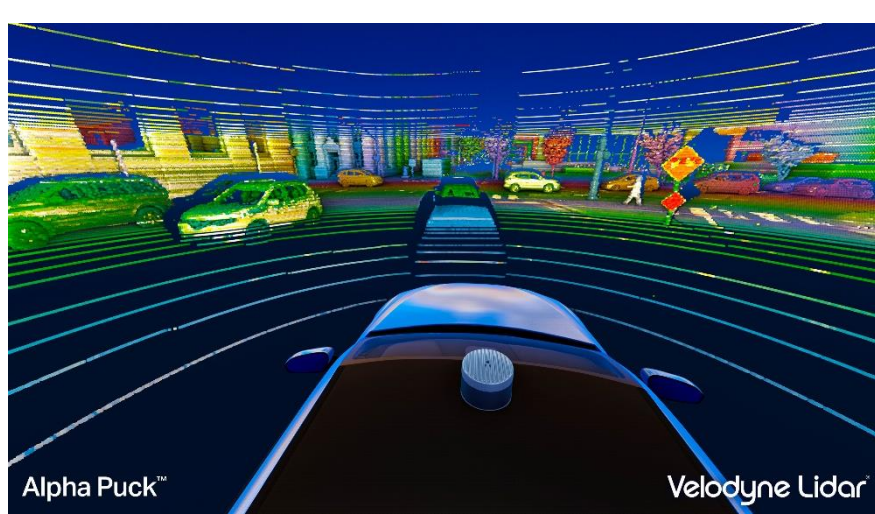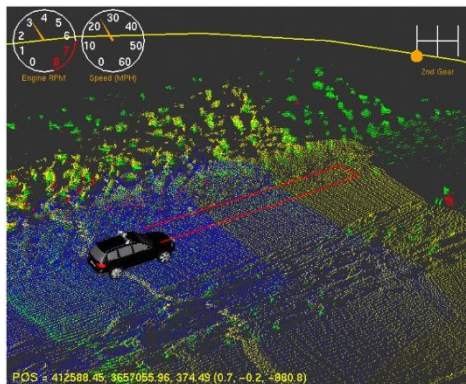
Radar sensors monitor the position of other vehicles nearby. Such sensors are already used in adaptive cruise-control systems

Components in Driverless Cars

Thakurdesai, Hrishikesh & Aghav, Jagannath. (2021). Autonomous Cars: Technical Challenges and a Solution to Blind Spot.
Components of Driver-less Car
(Source: The Economist,
How does a self-driving car work)

Fire detection sensors

- **Physical principle**

  Detect flame by sensing ultraviolet light

- **Flame detector, fire alarms, fire fighting competitions, etc**

- **Can detect a flame from a cigarette lighter from a distance of more than 5m**
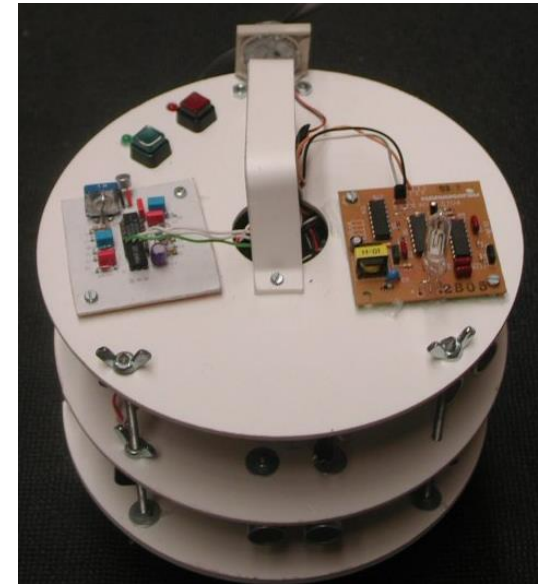
Compass

- **Physical principle**

  Detection of Earth magnetic field

- **Used to detect robot orientation**

- **Together with velocity information can be used for dead reckoning**

- **Resolution 1º, Accuracy 2º**

- **Sensitive to other magnetic fields ot metal in the environment**
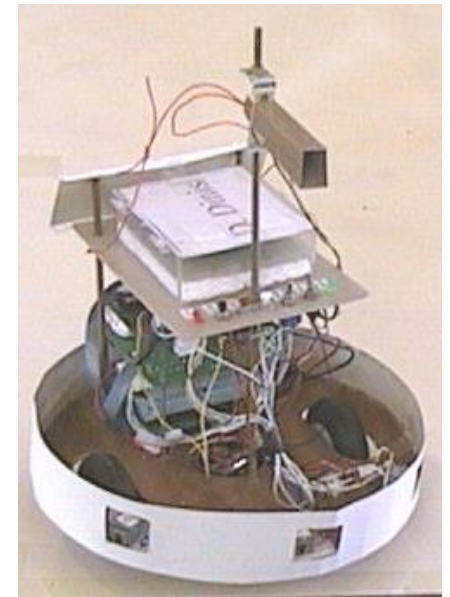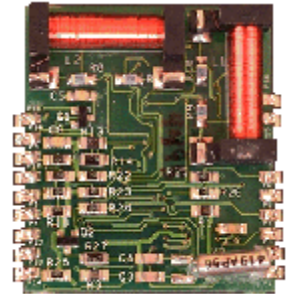
Inertial sensors

- **Accelerometer**
  - Measures the linear acceleration of the robot
  - Second integration to obtain displacement

- **Gyroscope**
  - Measures the angular motion of the robot
  - Not influenced by gravity
  - Integration gives angular displacement

DE-ACCM3D
3 axis accelerometer board

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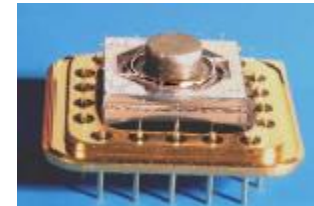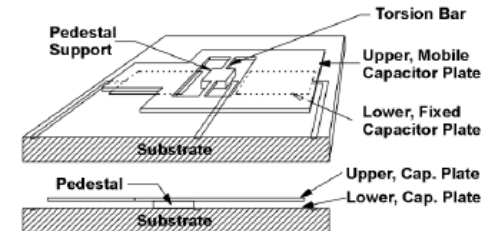
Multisensor fusion

- **Redundant**
  - Several sensors return the same percept
- **Complementary**
  - Provide disjoint types of information about percept
- **Coordinated**
  - Sequence of sensors
  - Focus-of-attention

Redundant Multisensor fusion

- **Mean of several measures**
  - Considering a normal distribution:

The mean of N measures as a reduced covariance

$$M \sim N(\mu, \sigma^2)$$

$$Mean = 1/N \sum_{n=1}^{N} M_i$$

$$Mean \sim N\left(\mu, \sigma^2/N\right)$$

Sensor Fusion

- **Kalman filter**
  - Integration of measures over time
  - Markovian assumption
  - Considers physics model and action model

  - Predict step

$$x_t = Px_{t-1} + Cu_t + q$$
$$z_t = Hx_t + r$$

$$q \quad N(0, Q)$$
$$r \quad N(0, R)$$
$$N(\hat{x}_{t-1}, \Sigma_{t-1})$$

  - Information

$$\bar{x}_t = P\hat{x}_{t-1} + Cu_t$$
$$\bar{\Sigma}_t = P\Sigma_{t-1}P^{\mathrm{T}} + Q$$

$$K_t = \bar{\Sigma}_t H^{\mathrm{T}}(H\bar{\Sigma}_t H^{\mathrm{T}} + R)^{-1}$$
$$\Sigma_t = (I - K_t H)\bar{\Sigma}_t$$
$$\hat{x}_t = \bar{x}_t + K_t(z_t - H\bar{x}_t)$$

Predict Stage	Update Stage
	Kalman Gain Calculation: $K(k) = P(k^-)H^T(HP(k^-)H^T + R(k))^{-1}$
Propagate State: $x(k^-) = \Phi x(k-1) + Bu(k-1)$	State Update with new Measure: $x(k) = x(k^-) + K(k)(y(k) - Hx(k^-))$
Propagate Co-Variance: $P(k^-) = \Phi P(k-1)\Phi^T + Q(k)$	Update Covariance with new measurement: $P(k) = (I - K(k)H)P(k^-)$

Initial Estimates: x_0, P_0

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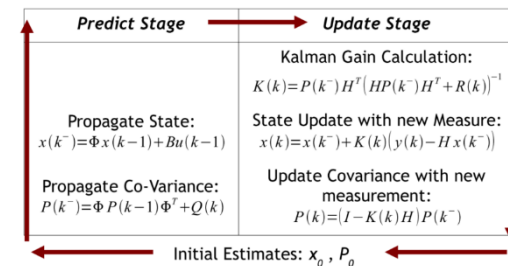
EKF

$$\begin{cases} \dfrac{d\,x(t)}{dt} & = & Ax(t)+Bu(t) \\ y(t) & = & Cx(t) \end{cases}$$

$$x=\begin{bmatrix} x_1 & x_2 \cdots x_m \end{bmatrix}^T \qquad dim(A)=m\times m$$

$$u=\begin{bmatrix} u_1 & u_2 \cdots u_p \end{bmatrix}^T \qquad dim(B)=p\times m$$

$$y=\begin{bmatrix} y_1 & y_2 \cdots y_q \end{bmatrix}^T \qquad dim(C)=m\times q$$

$$\begin{cases} x(k) & = & \Phi x(k-1)+Gu(k-1) \\ y(k) & = & Hx(k) \end{cases}$$

$$\Delta t_k = t_k - t_{k-1}$$
$$\Phi(k)=e^{A\Delta t_k}$$
$$G=\int_{t_{k-1}}^{t_k} e^{A\Delta t_k} B\, dt$$
$$H=C$$

EKF

$$\begin{cases} x(k) &= \Phi x(k-1) + Gu(k-1) + w(k-1) \\ y(t) &= Hx(k) + v(k-1) \end{cases}$$

$$R_w(k,i) = \begin{cases} Q(k) & se \quad i=k \\ 0 & se \quad i \neq k \end{cases}$$

$$E(w(k)v(i)^T)=0 \quad , \forall k, i$$

$$E(x(0))=X_0$$

$$R_v(k,i) = \begin{cases} R(k) & se \quad i=k \\ 0 & se \quad i \neq k \end{cases}$$

$$P(w) \sim N(0,Q)$$
$$P(v) \sim N(0,R)$$

$$cov(x(0))=P_0$$

Kalman Filter always keeps track of **averages** and **covariances** !

$$P \Rightarrow \sigma^2 = \begin{bmatrix} cov(y_1,y_1) & cov(y_1,y_2) & \cdots & cov(y_1,y_n) \\ cov(y_2,y_1) & cov(y_1,y_1) & \cdots & cov(y_1,y_n) \\ \vdots & \vdots & \ddots & \vdots \\ cov(y_n,y_1) & cov(y_1,y_1) & \cdots & cov(y_n,y_n) \end{bmatrix}$$

EKF

```
Initial(State, Covariance)

Cycle:

    Propagate (Stat,Covar,SysModel,Inputs)
    Cycle Meas(i):
        If Valid(Meas(i)) then
            Update(Stat,Covar,MeasModel(i),Meas(i))
```
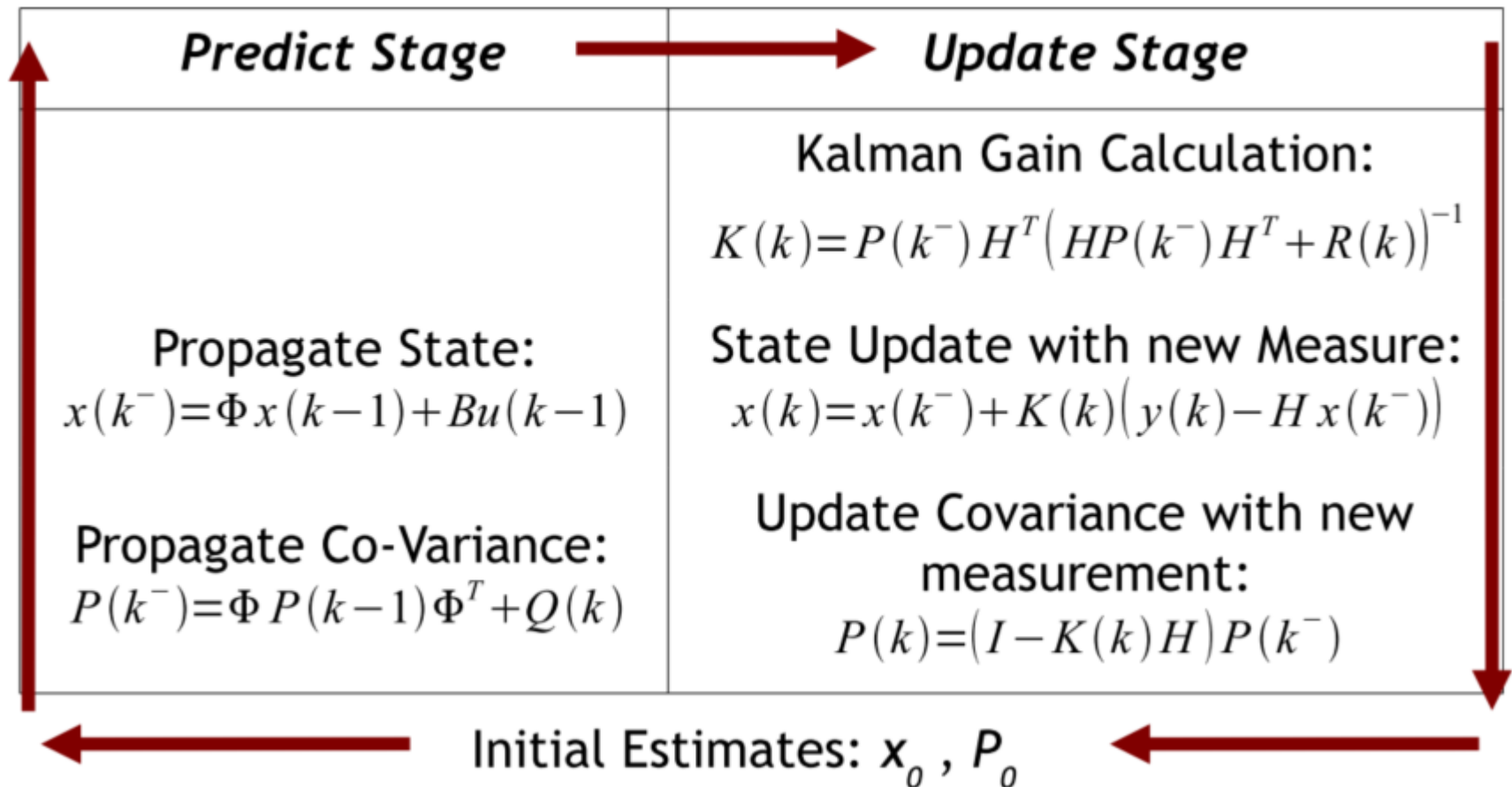
This is an abuse => no guarantees!

EKF

$$\frac{d X(t)}{dt} = f(X(t), u(t_k), t), \quad t \in]t_{k-1}, t_k]$$

$$A_k = \frac{\partial f}{\partial x}\bigg|_{\substack{x = x(t_k) \\ u = u(t_k) \\ t = t_k}} \qquad A(k) = \exp\big(A_k(t_k - t_{k-1})\big)$$

$$
\begin{aligned}
x(k) &\approx \tilde{x}(k) + A\big(x(k-1) - \hat{x}(k)\big) + W\, w(k-1) \\
y(k) &\approx \tilde{y}(k) + h\big(x(k) - \tilde{x}(k)\big) + V\, v(k)
\end{aligned}
$$

$$A = \frac{\partial f}{\partial x} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \cdots & \frac{\partial f_2}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \frac{\partial f_n}{\partial x_2} & \cdots & \frac{\partial f_n}{\partial x_n} \end{bmatrix} \quad H = \frac{\partial h}{\partial x} = \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \frac{\partial h_1}{\partial h_2} & \cdots & \frac{\partial h_1}{\partial x_n} \\ \frac{\partial h_2}{\partial x_1} & \frac{\partial h_2}{\partial h_2} & \cdots & \frac{\partial h_2}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial h_q}{\partial x_1} & \frac{\partial h_q}{\partial h_2} & \cdots & \frac{\partial h_q}{\partial x_n} \end{bmatrix} \quad W = \frac{\partial f}{\partial w} = \begin{bmatrix} \frac{\partial f_1}{\partial w_1} & \frac{\partial f_1}{\partial w_2} & \cdots & \frac{\partial f_1}{\partial w_n} \\ \frac{\partial f_2}{\partial w_1} & \frac{\partial f_2}{\partial w_2} & \cdots & \frac{\partial f_2}{\partial w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial w_1} & \frac{\partial f_n}{\partial w_2} & \cdots & \frac{\partial f_n}{\partial w_n} \end{bmatrix} \quad V = \frac{\partial h}{\partial v} = \begin{bmatrix} \frac{\partial h_1}{\partial v_1} & \frac{\partial h_1}{\partial v_2} & \cdots & \frac{\partial h_1}{\partial v_n} \\ \frac{\partial h_2}{\partial v_1} & \frac{\partial h_2}{\partial v_2} & \cdots & \frac{\partial h_2}{\partial v_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial h_q}{\partial v_1} & \frac{\partial h_q}{\partial v_2} & \cdots & \frac{\partial h_q}{\partial v_n} \end{bmatrix}$$

EKF

Predict Stage →	Update Stage

Kalman Gain Calculation:

$$K(k) = P(k^-) H^T \left(H P(k^-) H^T + R(k) \right)^{-1}$$

Propagate State:

$$x(k^-) = \Phi x(k-1) + B u(k-1)$$

State Update with new Measure:

$$x(k) = x(k^-) + K(k) \left(y(k) - H x(k^-) \right)$$

Propagate Co-Variance:

$$P(k^-) = \Phi P(k-1) \Phi^T + Q(k)$$

Update Covariance with new measurement:

$$P(k) = (I - K(k) H) P(k^-)$$

Initial Estimates: x_0 , P_0

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EKF – Trouble

EKF offer no theoretical guarantees

    Not Optimal

    May not converge

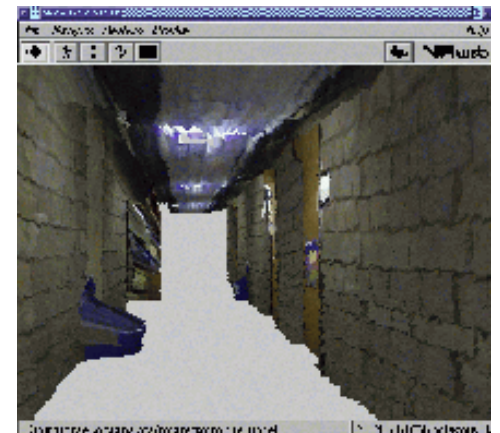   Expect troubles with periodical functions such as trigonometrical

Should:

    Design and implement VERY carefully

    Test thouroughly

Complementary Multisensor fusion

- **Example: Mercator Project**
  - The robot
    - 2 Laser ranger finders
    - 1 omnicam
  - Laser ranger finders are used to detect distance to walls and obstacles
  - Output of omnicam is used to apply textures to the model

Sensors

Luís Paulo Reis

lpreis@fe.up.pt
Director/Researcher LIACC
Associate Professor at FEUP/DEI

Armando Sousa

asousa@fe.up.pt
Researcher INESC-TEC
Assistant Professor at FEUP/DEEC

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