Sensors

Luís Paulo Reis

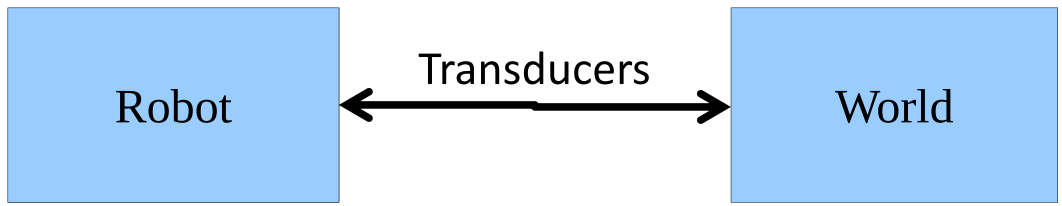
lpreis@fe.up.pt
Director/Researcher LIACC
Associate Professor at FEUP/DEI

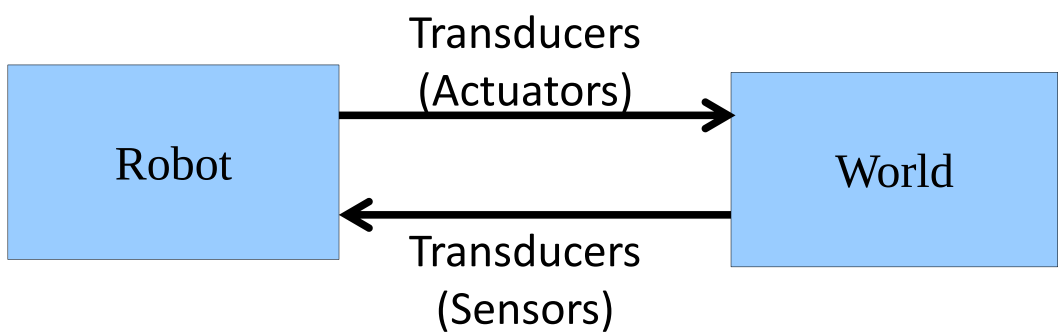
Armando Sousa

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


Robot
Transducers
World


Transducers
(Actuators)
Robot
World
Transducers
(Sensors)

The Perception Problem

- **Do we need perception?**
  - Complexity
  - Uncertainty
  - Dynamic World
  - Detection/Correction of errors
- **A robot must perceive its physical environment to get information about itself and its surroundings**

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

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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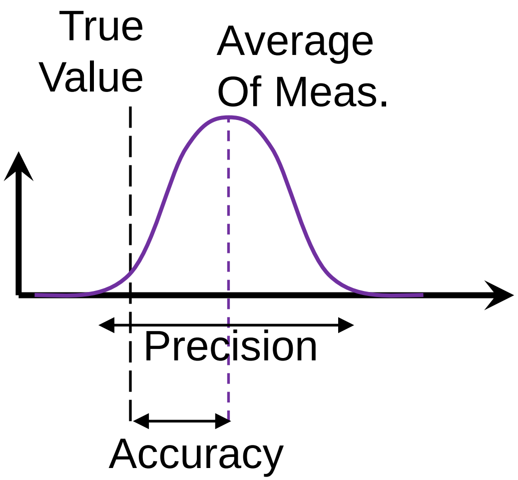
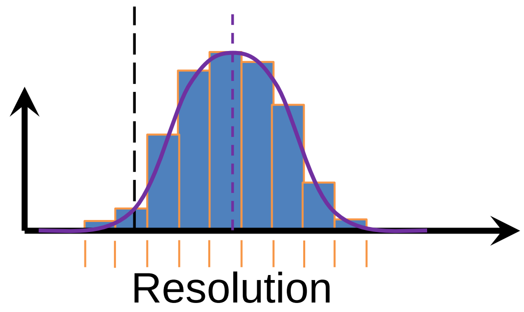
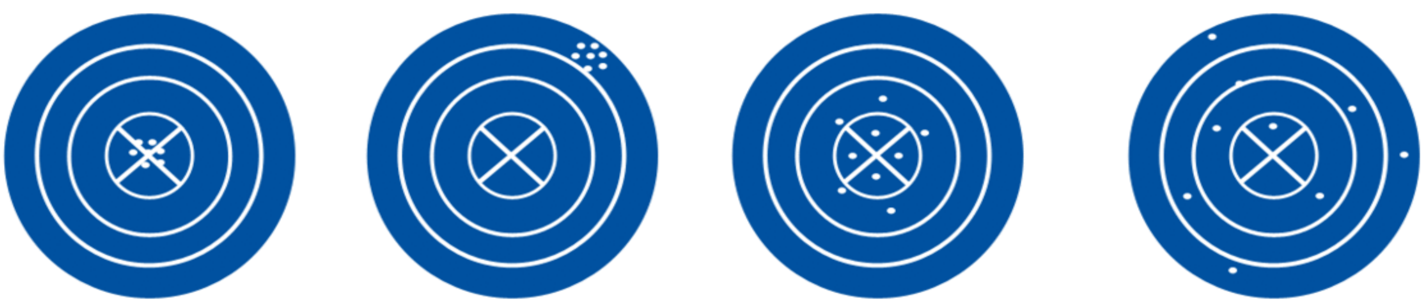
Sensor Characteristics

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

Accuracy…







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

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

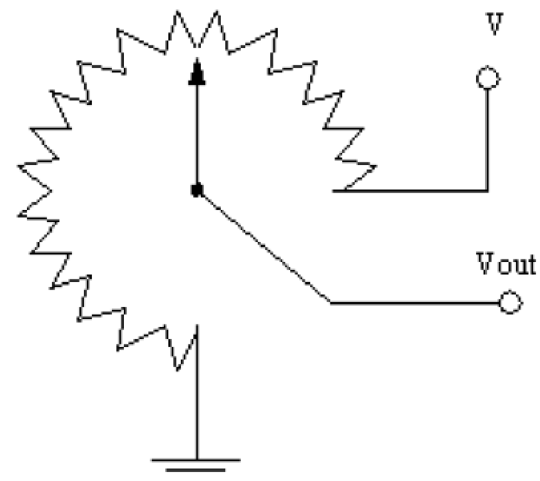
- Potentiometers
- Encoders
- Inertial navigation system
- Compass
- Gyroscopes
- Battery sensors

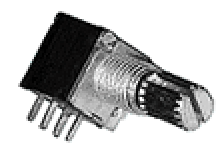
Potentiometer

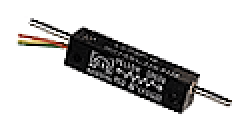
- **Physical principle:**

  Linear tension variation at the output of a variable resistance

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





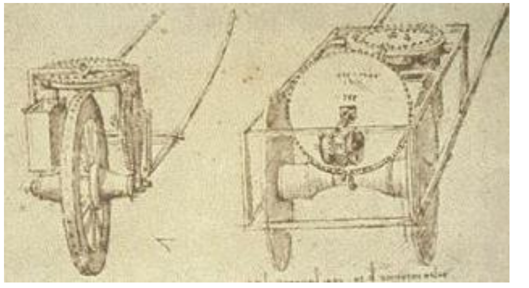


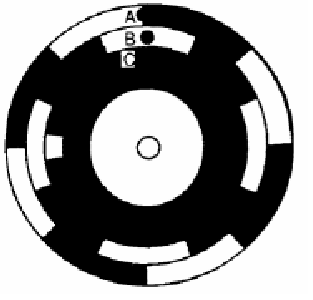
Encoders / Odometry

- **Physical principle**

  Record the wheel traversed distance

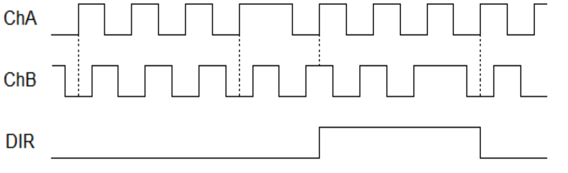
- **Wheel traversed distance is used to estimate robot position and orientation**





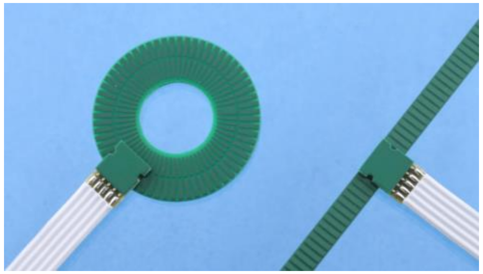
$$lin = \frac{v_l + v_r}{2}$$

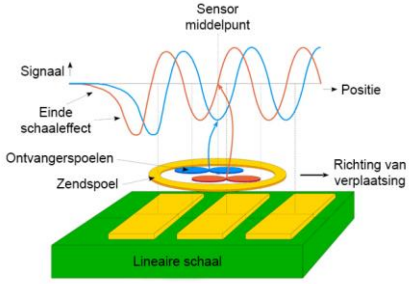
$$rot = \frac{v_l - v_r}{D}$$



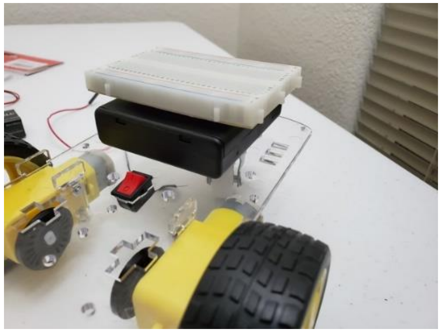
Detect direction of movement

Encoders / Odometry

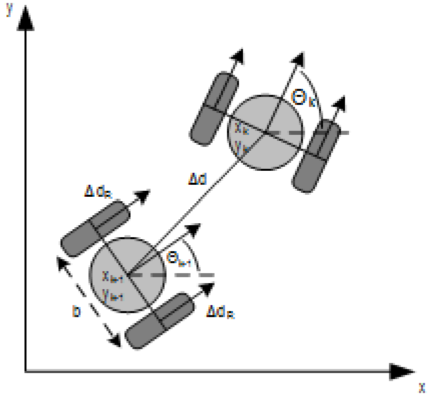




https://e.sentech.nl/en/news/inductive-encoder-accurately-measure-displacement-in-harsh-conditions



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



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 tc  uce errors
  – Resolution: few centimeters

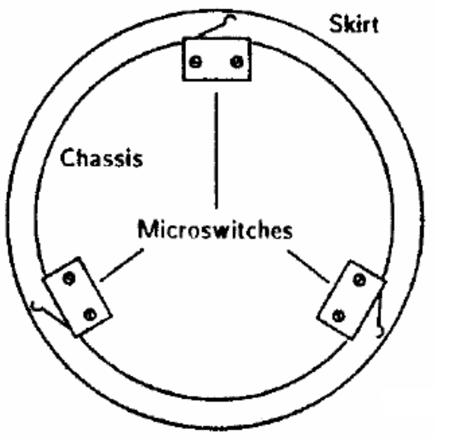
Proximity sensors

- **Bumper**
- **Infrared**
- **Sonar**
- **Laser Range Finder**

Bumper

- **Physical principle**

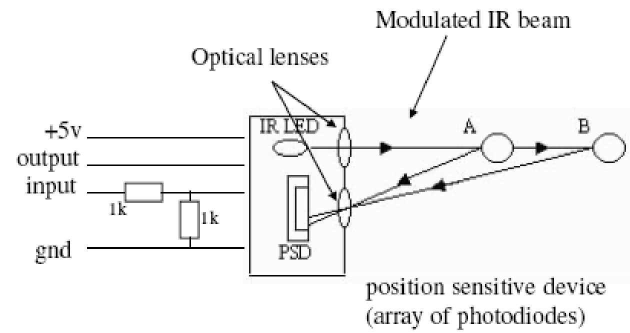
  Direct contact closes (or opens) a circuit
- **Used to detect collisions**
- **Binary value**
- **Reliable but the collision is eminent**

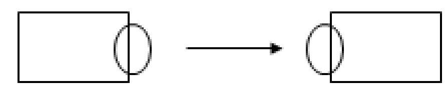


Infrared sensor

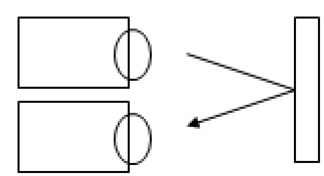
- **Physical principle**

  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**





IR barrier

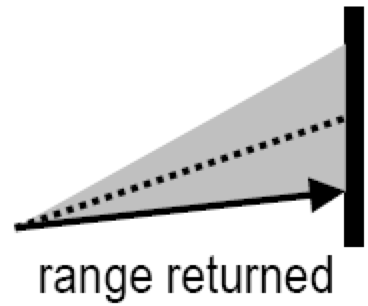


Sonar

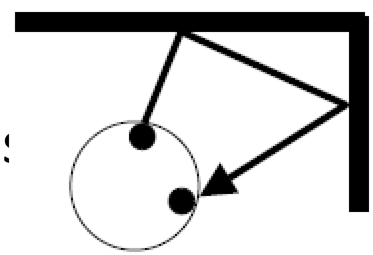
- **Physical principle**
  Emit US chirp, time until echo is received is used
  to estimate distance
- **Time until echo is proportional to the distance until cl**
  obstacle
  - Speed of sound changes with temperature
    and pressure
- **Range: few centimeters to ~10m**
- **Field of view ~30º**
- **Cheap (but not as cheap as IR)**
- **Fast (depends on range)**
- **Ring of sonars**

Sonar problems

- **Foreshortening**



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



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

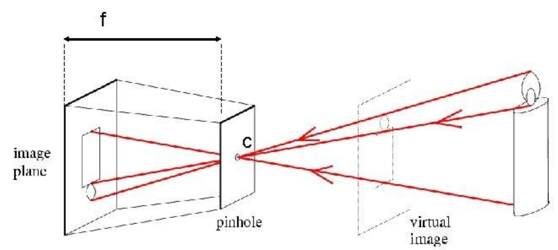
Laser range finder

- **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**

Vision

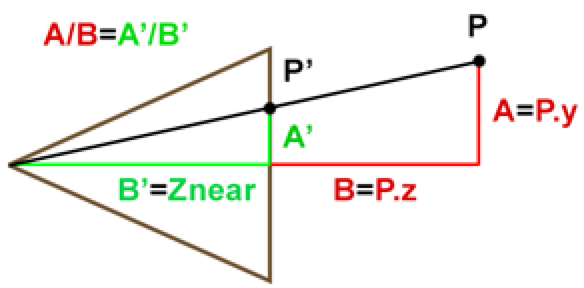
Pinhole camera



f = focal length
c = center of the camera

Figure from Forsyth

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



© 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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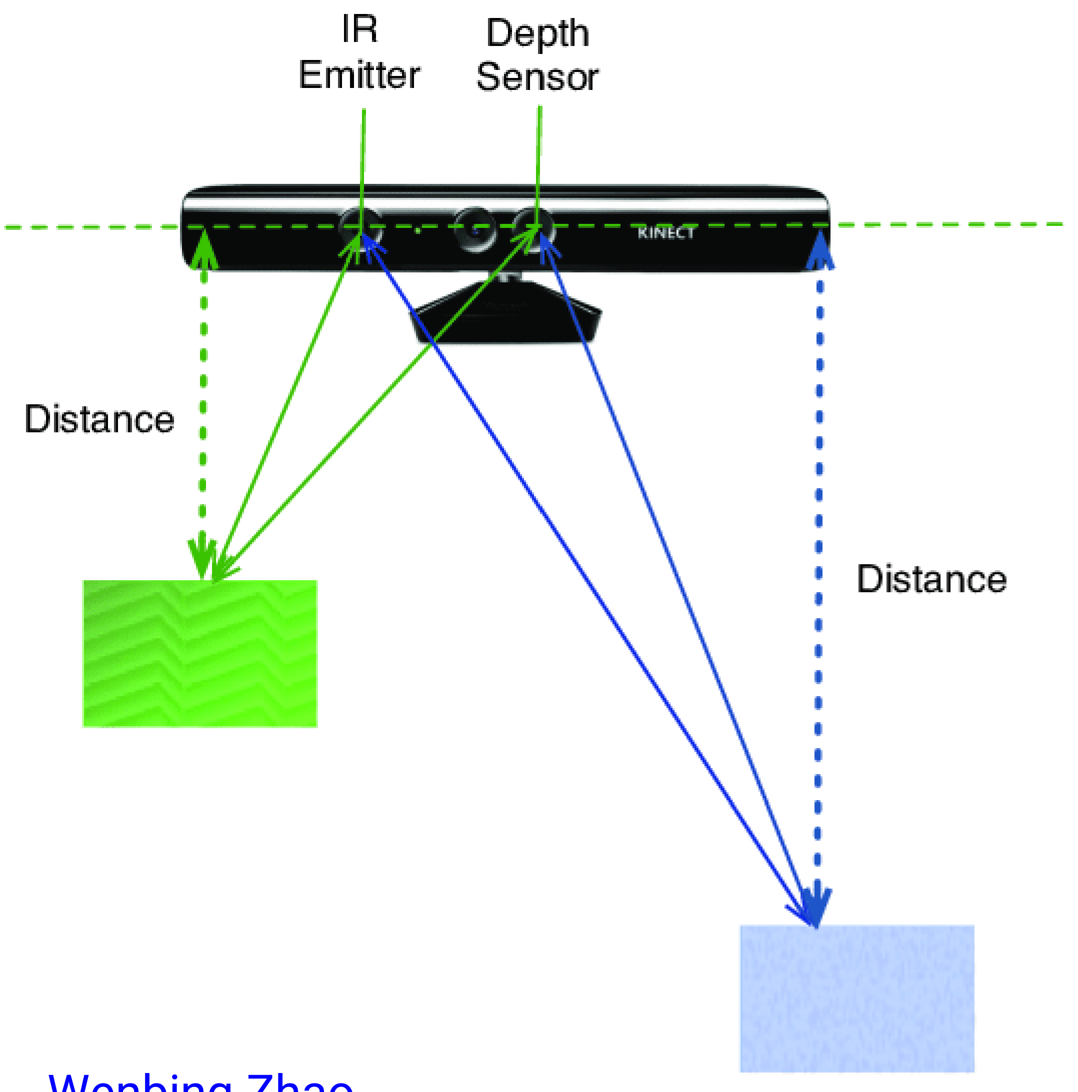
Depth Sensing



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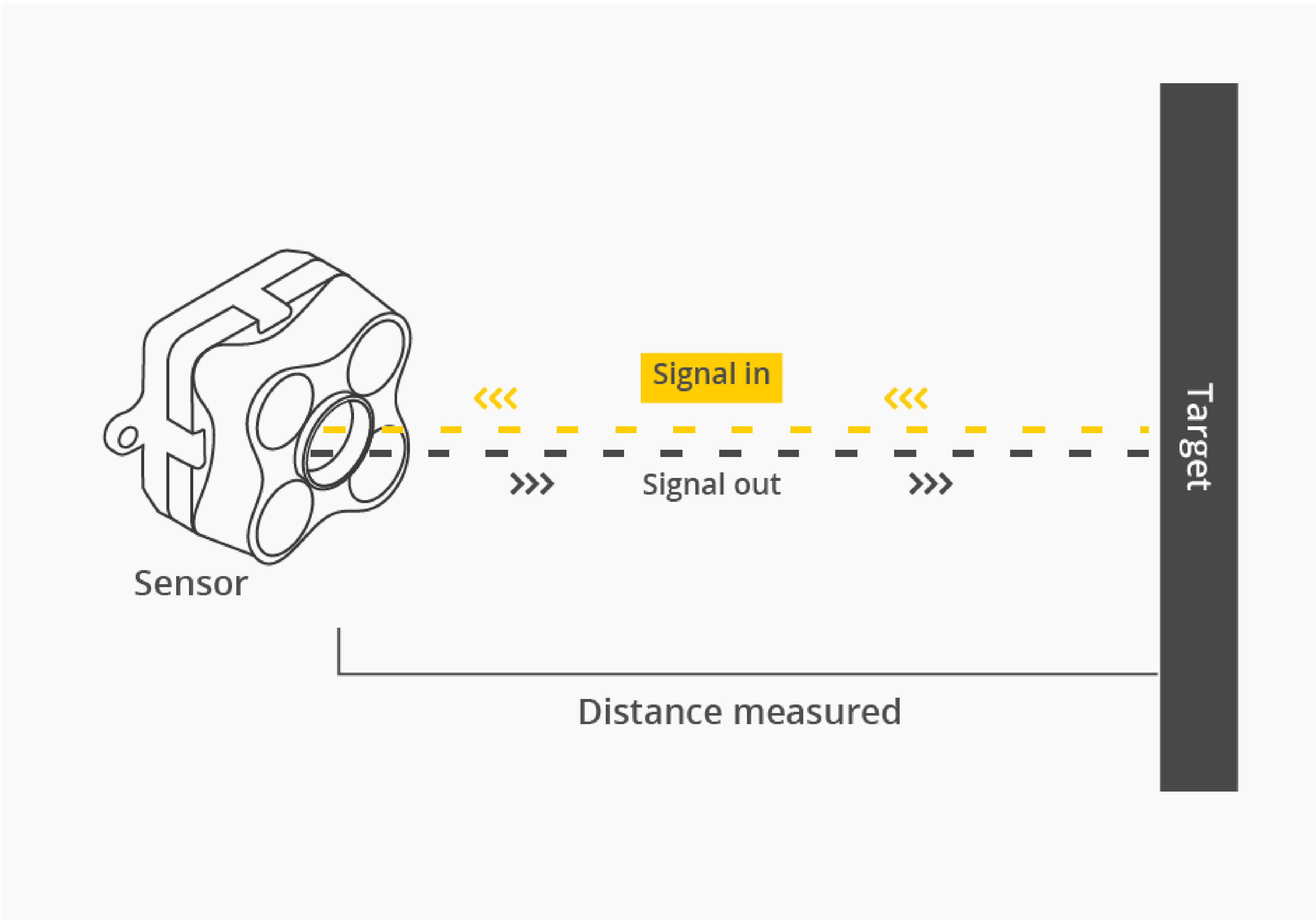
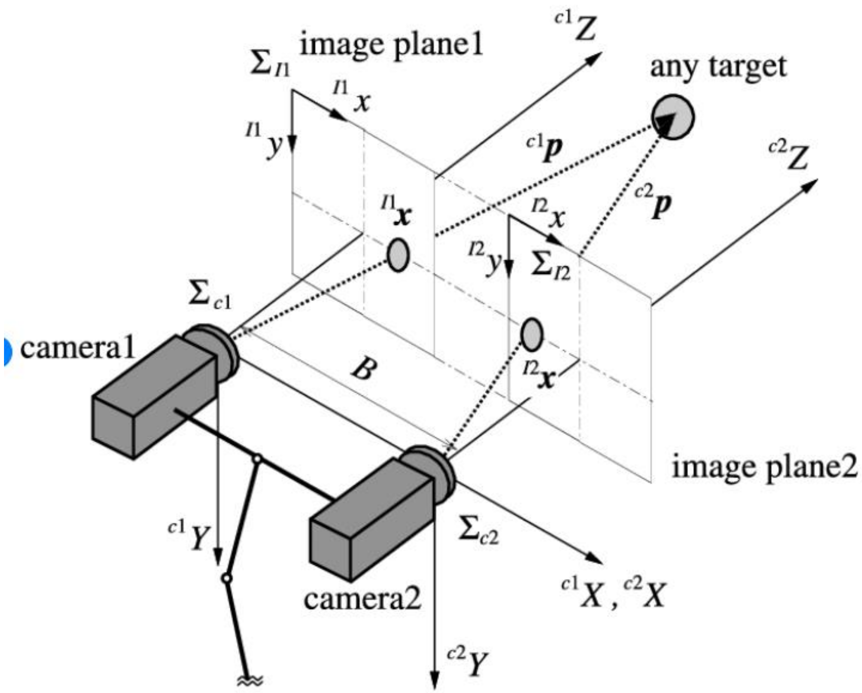
Wenbing Zhao

Depth Sensing



https://www.terabee.com/time-of-flight-principle/

Stereo Vision



STEREOLABS

Visual tracking of unknown moving object by adaptive binocular visual servoing 1999

DOI:[10.1109/MFI.1999.815998](https://doi.org/10.1109/MFI.1999.815998)

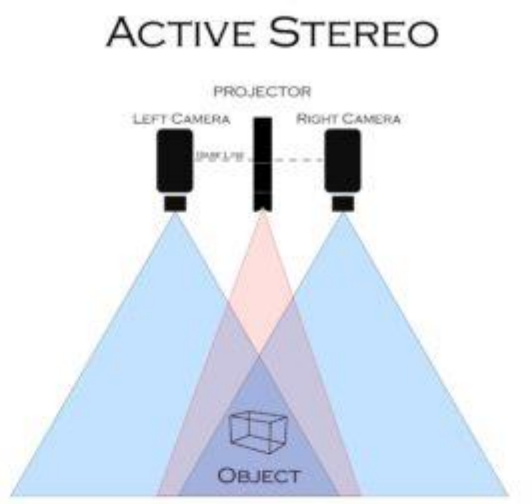
•IEEE Xplore

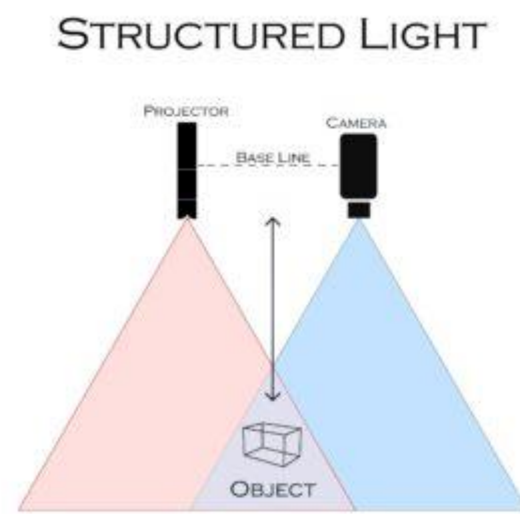
•Conference: Multisensor Fusion and Integration for Intelligent Systems, 1999

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

https://www.stereolabs.com/solutions/robotics/

Active Stereo



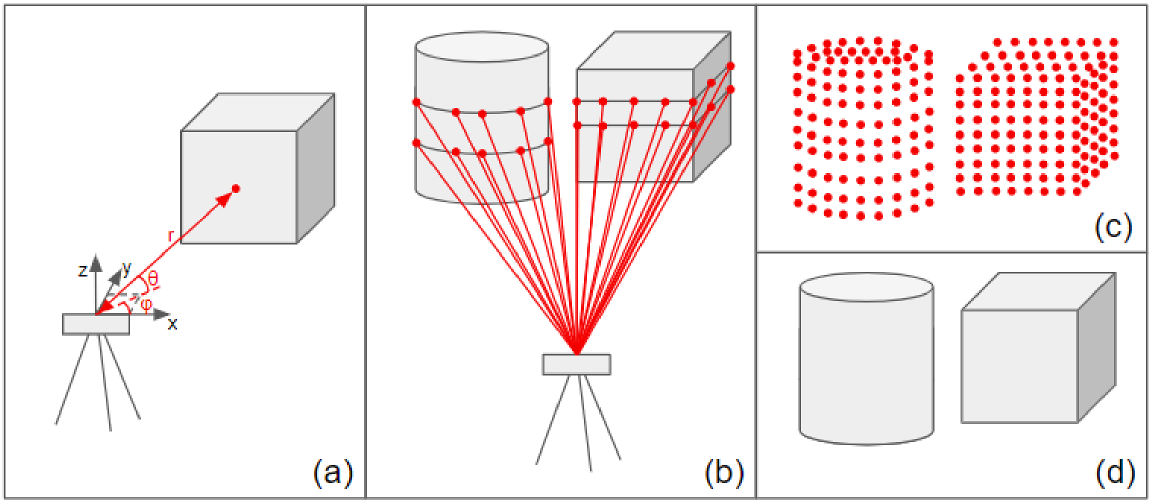


https://www.osela.com/depth-sensing/

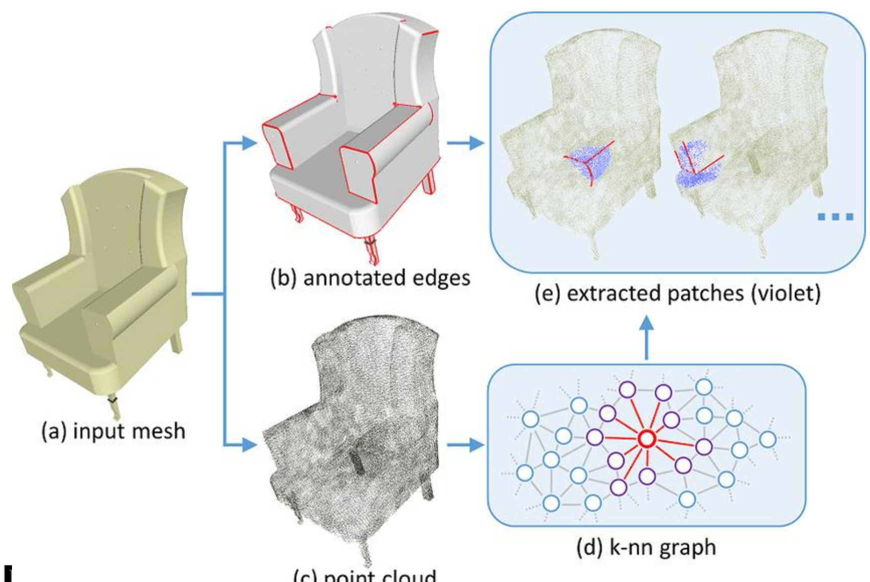
RGBD

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

RGBD – Point Cloud



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



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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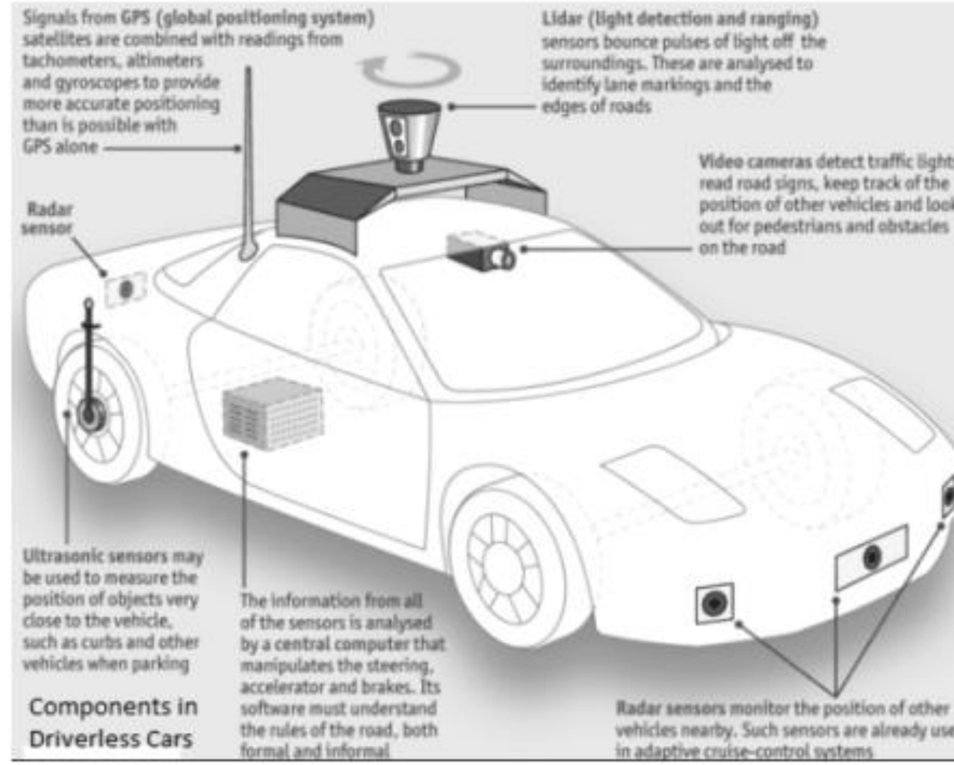
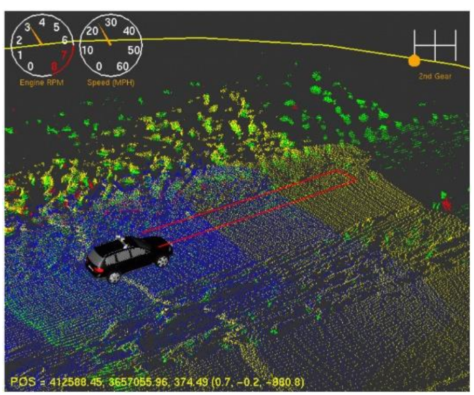
Automotive Sensors / LIDAR

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



[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)

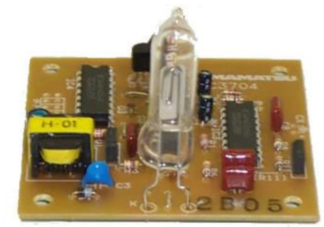


Thrun et al.

Fire detection sensors

- **Physical principle**

  Detect flame by sensing ultraviolet light

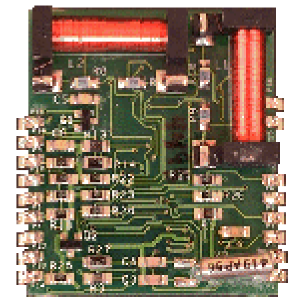


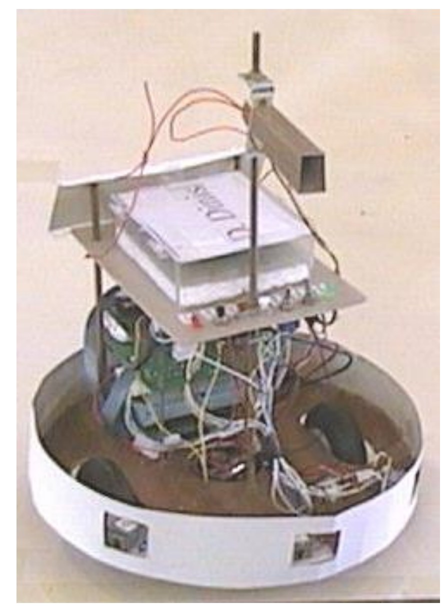
- **Flame detector, fire alarms, fire fighting competitions, etc**

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

Compass

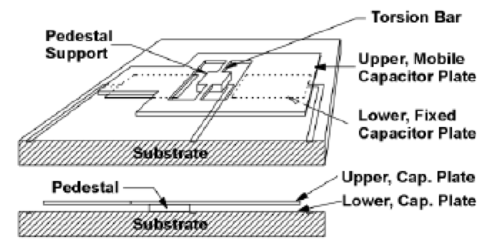
- **Physical principle**
  Detection of Earth magnetic field
- **Used to detect robot orientation**
- **Together with velocity information can be used for dead reckoning**
- **Resolution 1º, Accuracy 2º**
- **Sensitive to other magnetic fields ot metal in the environment**

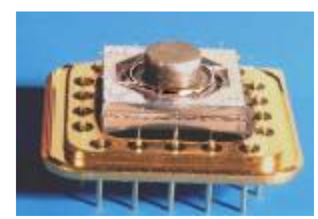




Inertial sensors

- **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





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

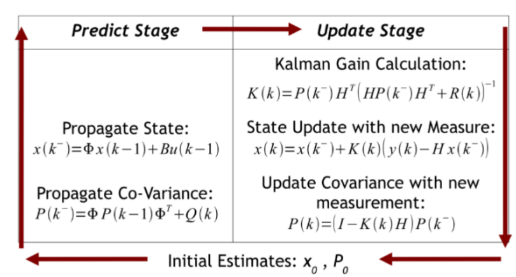
  - Predict step

$$x_t = Px_{t-1} + Cu_t + q \qquad q \quad N(0,Q)$$
$$z_t = Hx_t + r \qquad r \quad N(0,R)$$
$$N(\hat{x}_{t-1}, \Sigma_{t-1})$$

  - Information

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

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



EKF

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

$$x=[x_1 \;\; x_2 \cdots x_m]^T \qquad dim(A)=m\times m$$

$$u=[u_1 \;\; u_2 \cdots u_p]^T \qquad dim(B)=p\times m$$

$$y=[y_1 \;\; y_2 \cdots y_q]^T \qquad dim(C)=m\times q$$

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

$$\Delta t_k = t_k - t_{k-1}$$

$$\Phi(k)=e^{A\Delta t_k}$$

$$G=\int_{t_{k-1}}^{t_k} e^{A\Delta t_k} B\,dt$$

$$H=C$$

EKF

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

$$R_w(k, i) = \begin{cases} Q(k) & se \;\; i=k \\ 0 & se \;\; i \neq k \end{cases} \qquad E(w(k)v(i)^T) = 0 \;\; , \forall k, i \qquad E(x(0)) = X_0$$

$$R_v(k, i) = \begin{cases} R(k) & se \;\; i=k \\ 0 & se \;\; i \neq k \end{cases} \qquad \begin{matrix} P(w) \sim N(0, Q) \\ P(v) \sim N(0, R) \end{matrix} \qquad cov(x(0)) = P_0$$

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

$$\frac{d X(t)}{dt}=f(X(t),u(t_k),t), \quad t\in]t_{k-1},t_k] \qquad A_k=\left.\frac{\partial f}{\partial x}\right|_{\substack{x=x(t_k)\\u=u(t_k)\\t=t_k}} \qquad A(k)=\exp\left(A_k(t_k-t_{k-1})\right)$$

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

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

EKF

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

Initial Estimates: x_0 , P_0

EKF – Trouble

EKF offer no theoretical guarantees

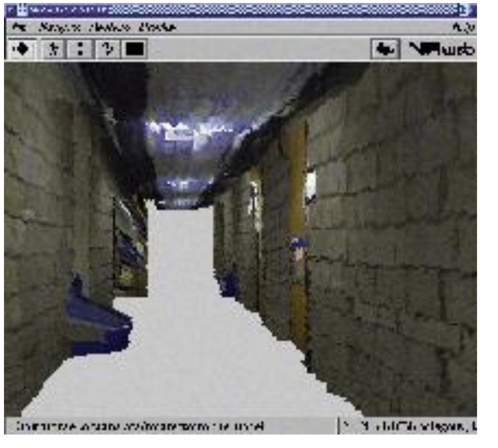
- Not Optimal
- May not converge
- Expect troubles with periodical functions such as trigonometrical

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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