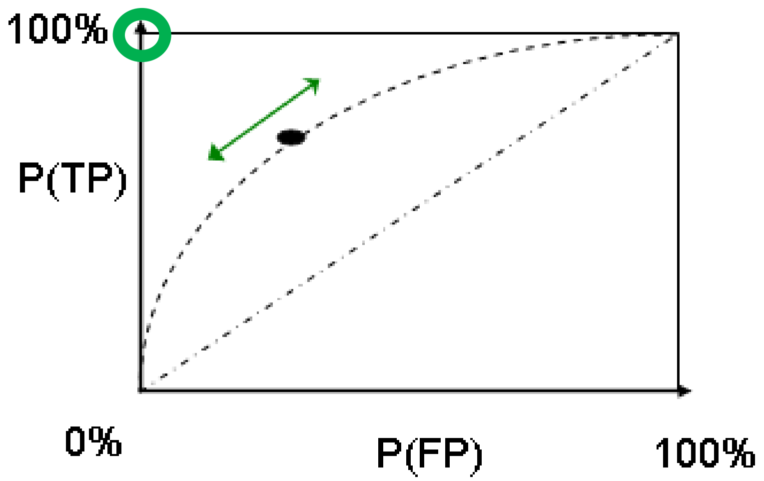
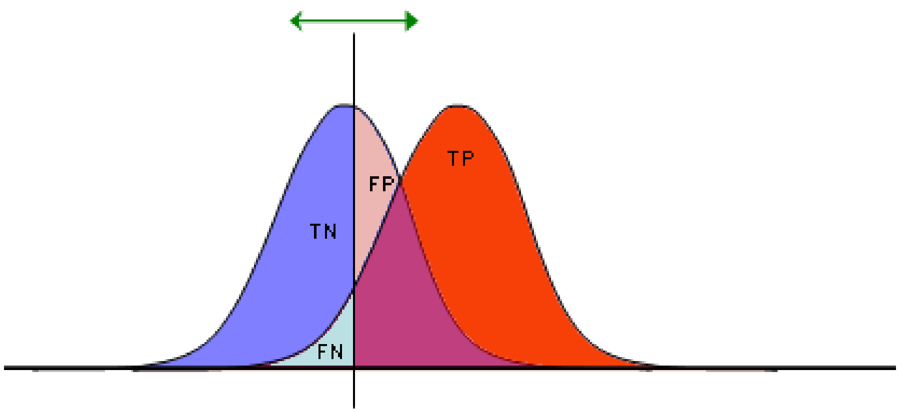
Robotics & Embedded Systems

Autonomes Fahren
SS 2019

AV Sensor-Sets





Technische Universität München

Robust Perception: Key issue for Avs … and humans

https://en.wikipedia.org/wiki/The_dress

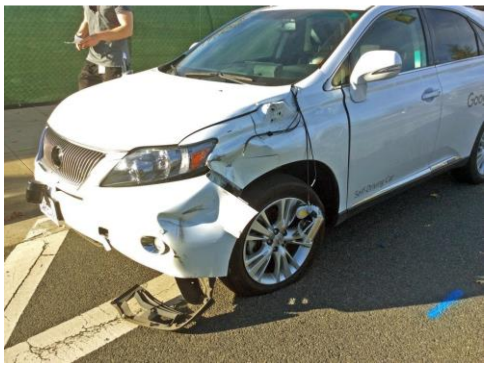
Autonomous Driving will change the world. A solution for many traffic problems.



Images of Waymo, Tesla and Uber vehicles

Strong progress has been made since the first AV inventions.

Autonomous Driving will change the world. A solution for many traffic problems.

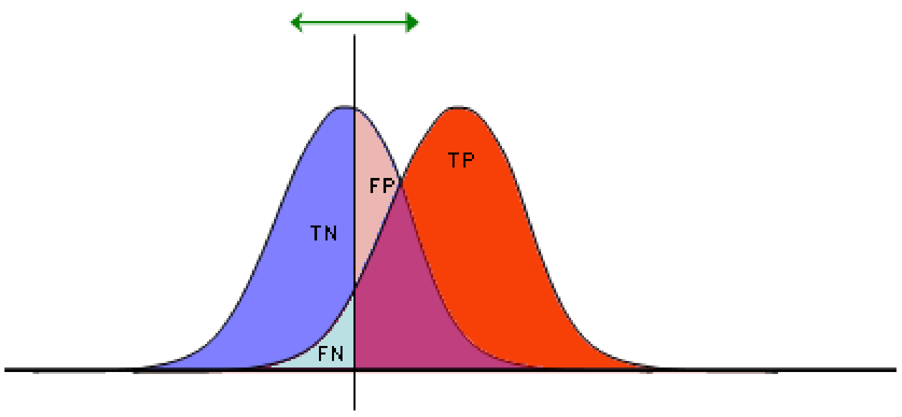


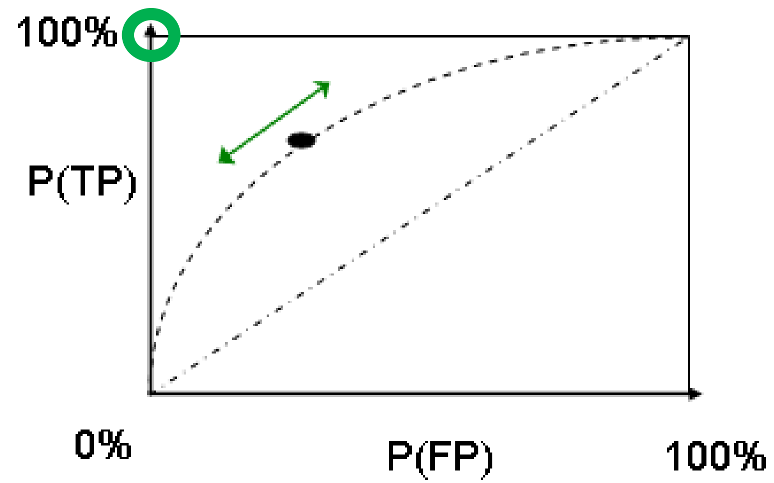
Images of Waymo, Tesla and Uber vehicles

However, many problems still remain.

The highest level of quality is required to achieve reliable autonomy.

AV technology will never be 100% error-free. Redundancy and safety monitoring are mandatory.





Receiver Operating Characteristic curve (ROC) represents AV challenge in one image.

Top left promises 100% True Positive, 0% False Positive detection, which is wanted, but never reached.

→ Without runtime monitoring, AVs will not work.

AV Sensor-Sets

- Automated cars require precise self-localization and localization of obstacles, lane markers, etc.
- Different sensors are available: Laser, Radar, Kamera, Ultraschall, GPS, Rain-sensors, thermal imaging…
- Which could you use and how are they different from each other?

*derivative work: Altair78 (talk) Lexus-LS600h-L_asia_spec.jpg: Tim Wang CC BY-SA 2.0, Wiki

AV Sensor-Sets

- Sensor performance depends on the sensors, the signal propagation and the target properties
- This lecture will serve as an introduction to a variety of properties for sensors, targets and propagation, based on public literature
- Examples (lidar) will be used to highlight important aspects

Sensor Categorization

Active or passive Sensors:

- Sensor are often sorted into active and passive sensors

Passive Sensor:

A passive sensor is an instrument designed to receive and measure emissions or reflections.

…Camera, electric field sensing, acceleration measurement…

Active Sensor:

An active sensor is an instrument used for measuring signals reflected by the sensor that were reflected, refracted or scattered.

…Radar, Laser, Ultrasound, GPS…

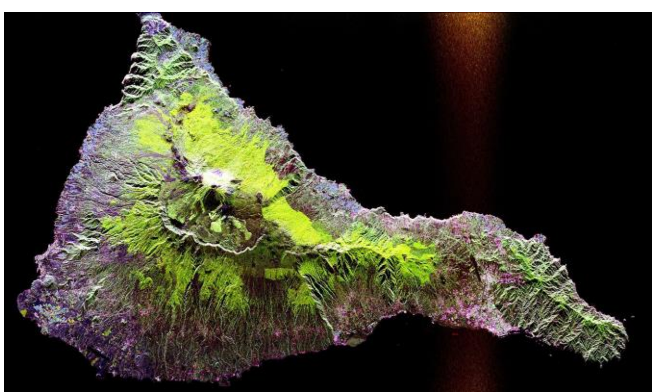
… smart camera with car light?

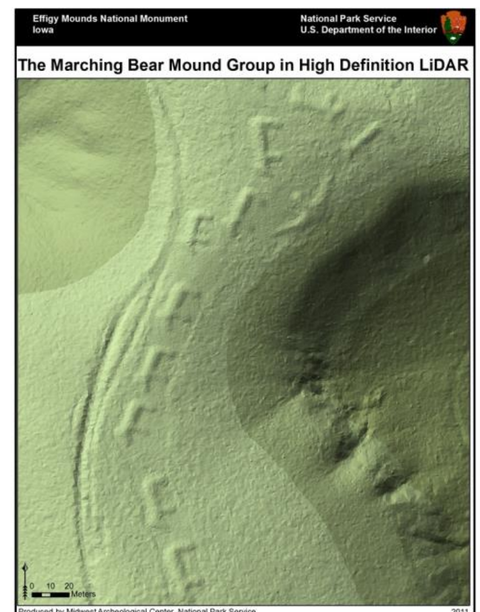
AV Sensor-Sets

Imaging Sensor?

Does the sensor detect and convey the information to form an image? …Camera…

…Lidar? …Radar? …Ultrasound?





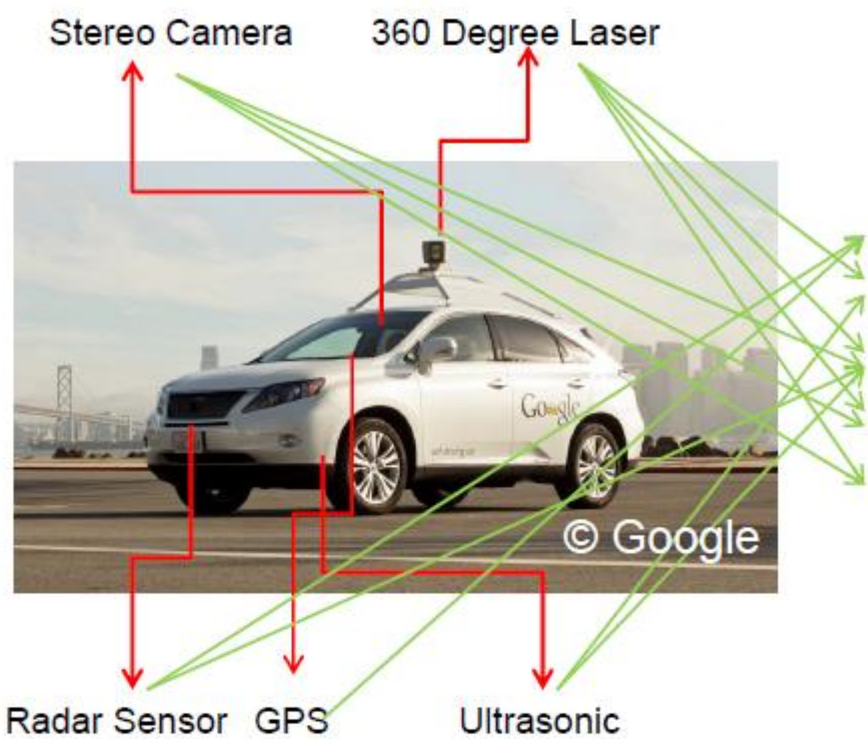
AV Sensor-Sets

K. Fuerstenberg et al.: "Pedestrian Recognition and Tracking of Vehicles using a vehicle based Multilayer Laserscanner", Intelligent Vehicle Symposium, IEEE (Volume:1), 2002

Segment				
Video image				
Distance	10 m	18 m	42 m	79 m

Example for sensor challenges: Limited angular resolution. Certainty of object type identification decreases with distance. Small objects can be missed between LIDAR beams.

AV Sensor-Sets



Information Extraction-----Useful Features

- ✓ Location – "It's in front of me"
- ✓ Range – "It's really close"
- ✓ Range rate – "It's coming closer"
- ✓ Size – "It's really big"
- ✓ Classification – "It's a semi truck"

AV Sensor-Sets

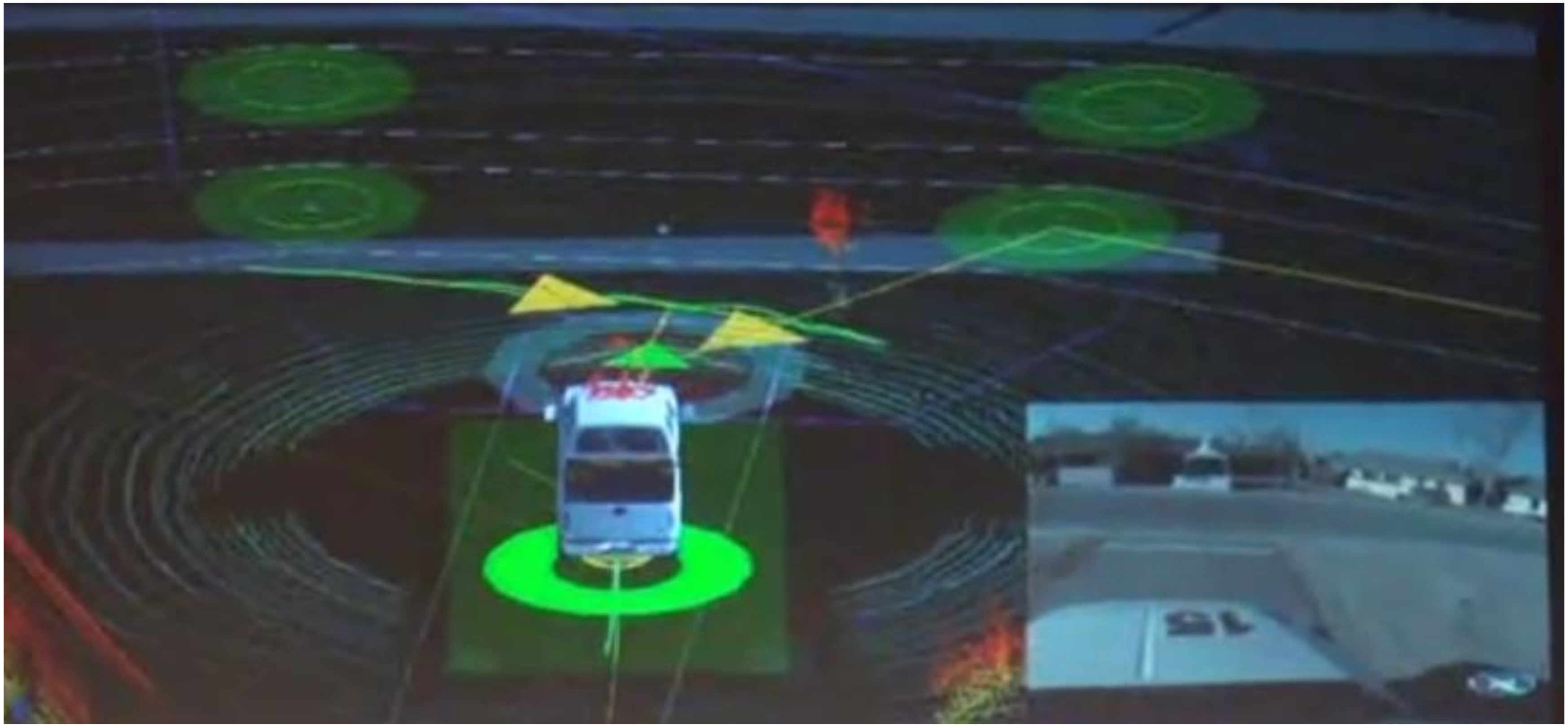
- Often tresholds are used to differentiate between detection and none-detection.
- Search for peaks in a detected signal to separate detections from noise
- Note: None-adaptive sensing thresholds regularly cause issues
  - Known accidents due to mismatching stationary vs non-stationary targets
  - Known issues due to false heigth classification (see curb stone video)

Velodyne LIDAR in Grand Challenge

Filmed at NIST
February 13, 2008

www.Society of Robots.com

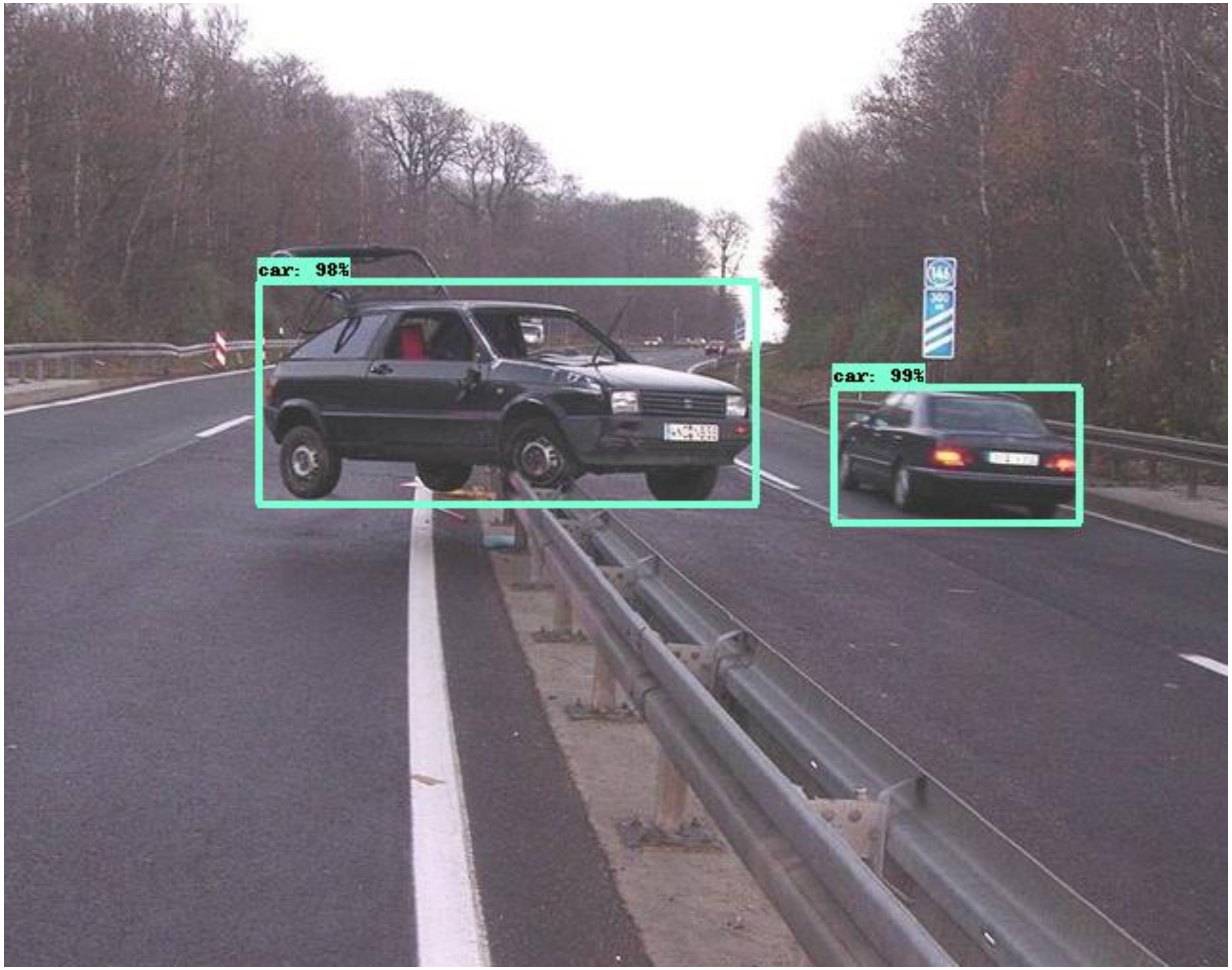
Failed threshold classification



"Rain gutter mistaken for curb stone"

From „Velodyne Lidar in Grand Challenge", youtube 2008

Assumptions are easily violated



Vehicles can occur in uncommon positions and orientations, but still need to get detected.

Sensor Datasheets

ibeo LUX 8L (Prototype) – Technical facts…

automotive

Laser	
• Laser class:	Class 1, Eye safe
• Wave length:	905 nm
• Technology:	Time of flight Output of distance and echo pulse width
• Range:	200 m (average target, 0 deg view direction)
Measurement	
• Horizontal field of view:	110 deg (50 deg to -60 deg)
• Vertical field of view:	6.4 deg (0 deg view direction)
• Multi layer:	8 layers (2 pairs of 4 layers)
• Multi echo:	Up to 3 distance measurements per laser pulse (allow measurements through atmospheric clutter like rain and dust)
• Data update rate: layers	6.25/ 12.5/ 25 Hz, valid for both alternate scanning pairs of
• Operating temperature range:	-40 to 85 deg C/ -40 to 185 deg F
• Accuracy (distance independent):	10 cm/ 3.9 in
• Angular resolution: H	orizontal: up to 0.125 deg
• Vertical:	0.8 deg
• Distance resolution:	cm/ 1.57 in
Software (embedded)	
• Raw data pre processing:	All measurements will be classified and tagged as valid/ ground/ clutter (available @ 6.25 Hz only)
• Real time object tracking:	Object properties: position, size, speed (available @ 6.25 Hz only)
• Ego motion compensation:	Vehicle ego motion data via CAN required

Sensor Datasheets

Mechanical/ Electrical

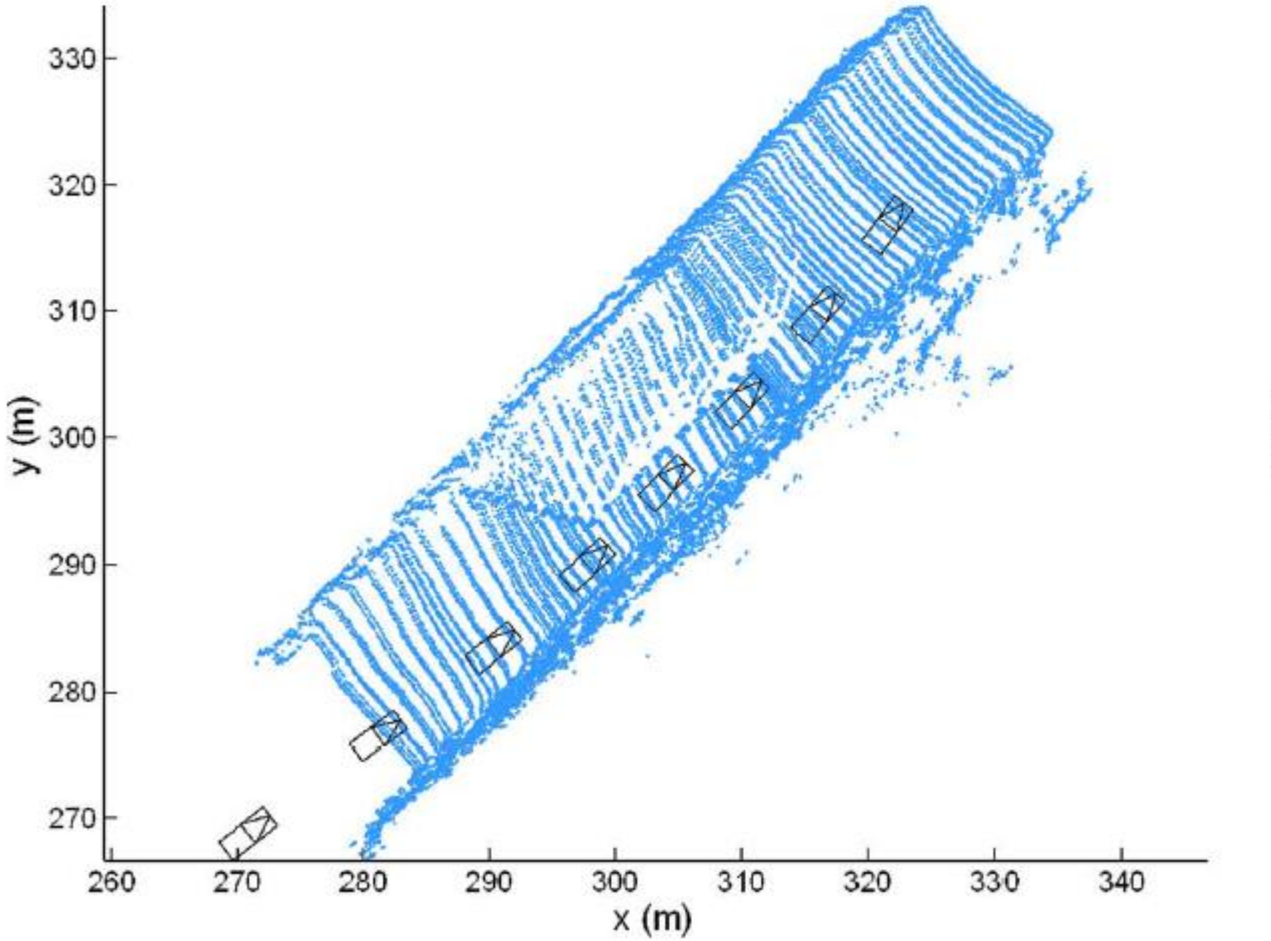
• Power supply:	9 to 27 V
• Power consumption:	8 W (average), < 10 W (max)
• Dimensions (W x D x H):	164.5 x 93.2 x 88 mm³/ 6.4 7 x 3.67 x 3.46 in³
• Protection class:	IP 69 K (IEC 60529, DIN 40050-9 (using protected plug connectors)) IP 68 (IEC 60529 (2 m, 24 h))

Data I/O

• 100 MBit Ethernet:	Output:Raw- and object data Input: Configuration/ time sync via NTP server
• CAN:	Output: Object data Input: Ego motion data
• RS232:	Sync

Sensor Artifacts

Lines typical sign of lidar image

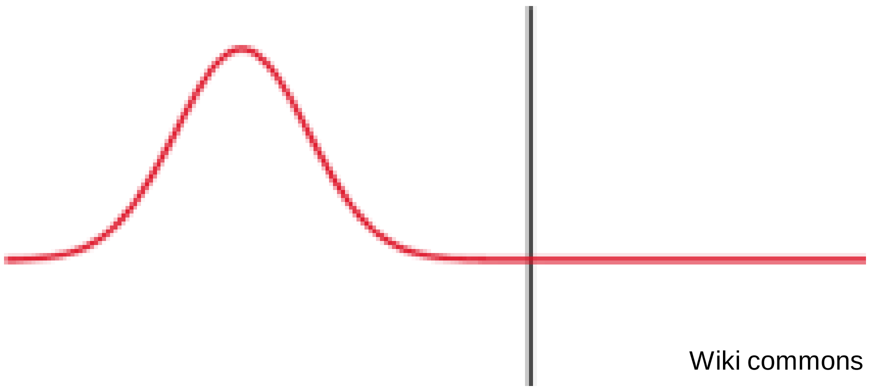


Jaehyun Han, Dongchul Kim, Minchae Lee, and Myoungho Sunwoo, „Enhanced Road Boundary and Obstacle Detection Using a Downward-Looking LIDAR Sensor", IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, VOL. 61, NO. 3, MARCH 2012

Introduction to sensor physics

Signal propagation:

- Refraction
- Reflection
- Scattering
- Absorption
- Transmission
- Diffraction
- Attenuation

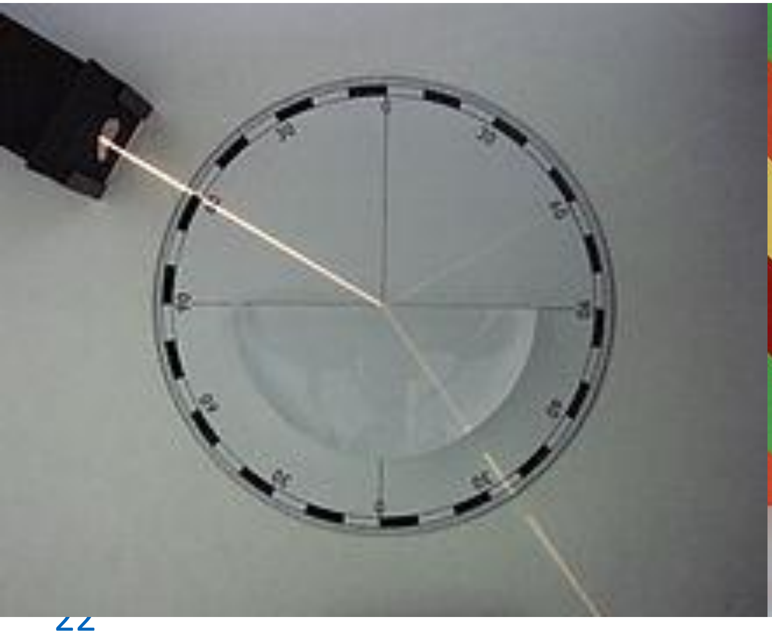


Wiki commons

Introduction to sensor physics

- Refraction: wave crossing from one medium into another, experiencing a change in direction, while continuing to travel through the new medium.

$$\frac{\sin\theta_1}{\sin\theta_2} = \frac{v_1}{v_2} = \frac{n_2}{n_1}.$$



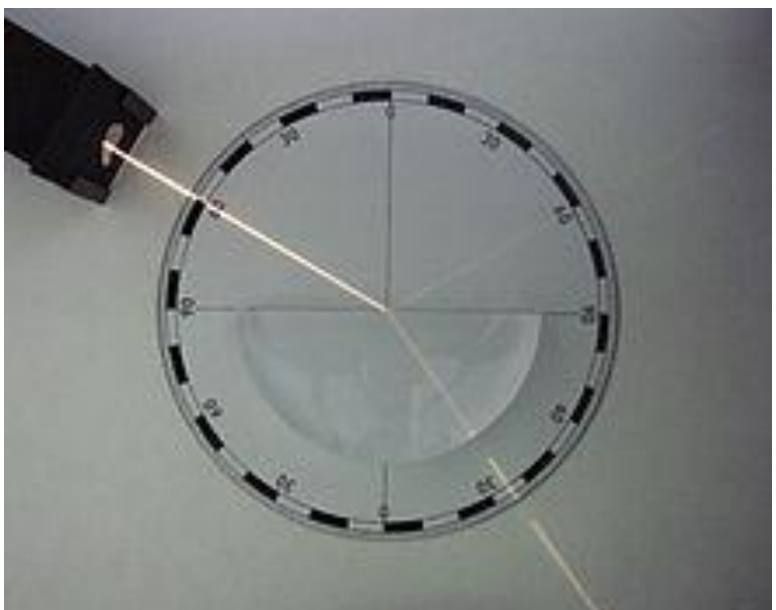
https://commons.wikimedia.org

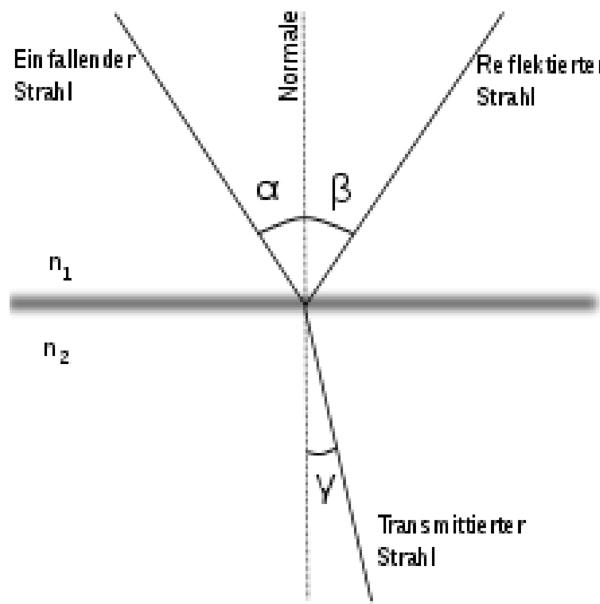
Zátonyi Sándor (ifj.)

JrPol -

Introduction to sensor physics

- Reflection: Change in direction of a wave, between two different media, with outgoing angle equal to the incident angle on the other side of the surfaces normal.



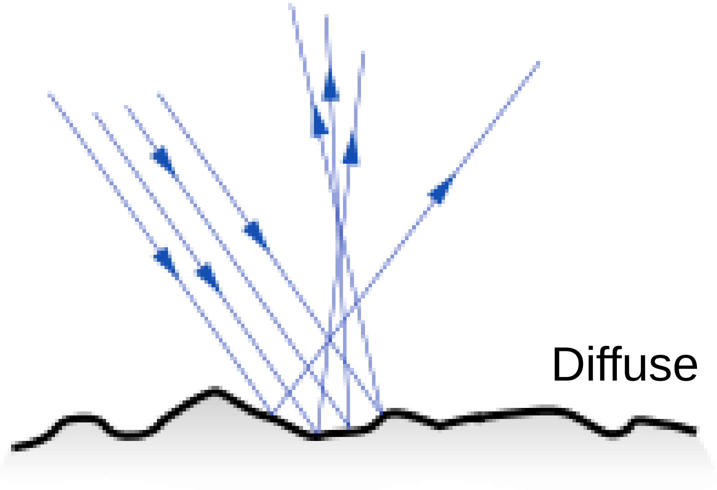


Introduction to sensor physics

Diffuse or specular reflection?

Depending on surface roughness and signal wave length

Specular



Diffuse

Introduction to sensor physics

Actual reflections depend on specific scenario.

Comparison of dry and wet street

Introduction to sensor physics

- Scattering: radiation such as light being forced to deviate from straight path due to localized non-uniformity in propagation medium

For example because of droplets or surface roughness (scattering centers)

Zodiacal light: glow originating from scattering of sunlight due to dust located between planets

Introduction to sensor physics

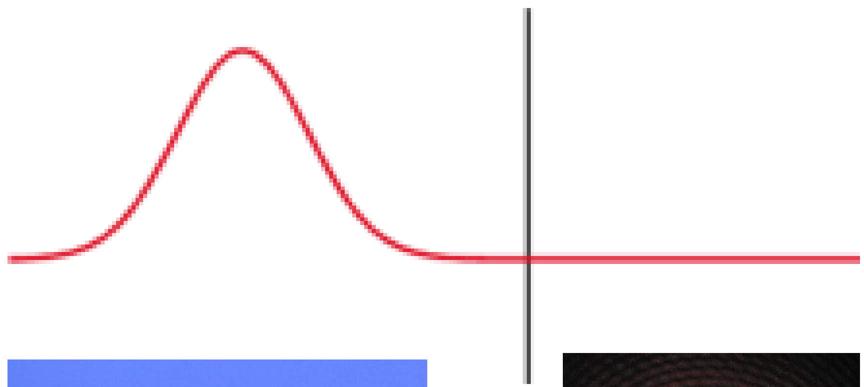
- Absorption: Loss of energy of propagating wave while traveling through a medium

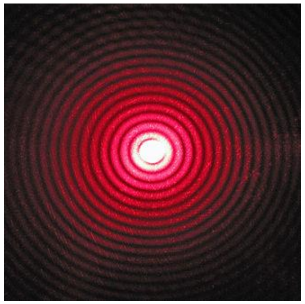
e.g. conversion into thermal energy in damping material (Ultrasound: foam; Light: carbon black) depends on depth, absorption coefficient…

Carbon black, by FK2051 wiki commons

Introduction to sensor physics

- Attenuation describes all losses in signal intensity, including scattering and absorption.
- Transmission: Propagating wave crosses from one medium into another and is transmitted through the medium
- Diffraction: Change of direction and intensities of waves, passing an obstacle or an aperture with size approximately the wavelength of the waves.





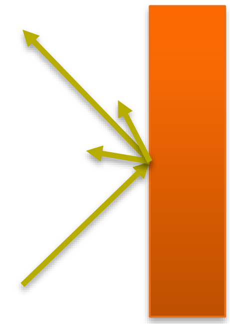
AV Sensor-Set Design Questions

- What do you want to measure and why?
- How do you measure it and why this way? Are their alternatives?
- How will you know if the measurement will be or was succesfull (metrics)? How accurate are your measurements?
- Do you have additional sensors for redundance?
- Documentation of reasoning, simulations, analysis and measurements
- Validate and verify (Do you have to correct requirements for the sensors? Do the sensors work as they are supposed to?)
- Does your approach fulfill norms for certification?

Robotics & Embedded Systems

AV Sensor-Set Detection Range

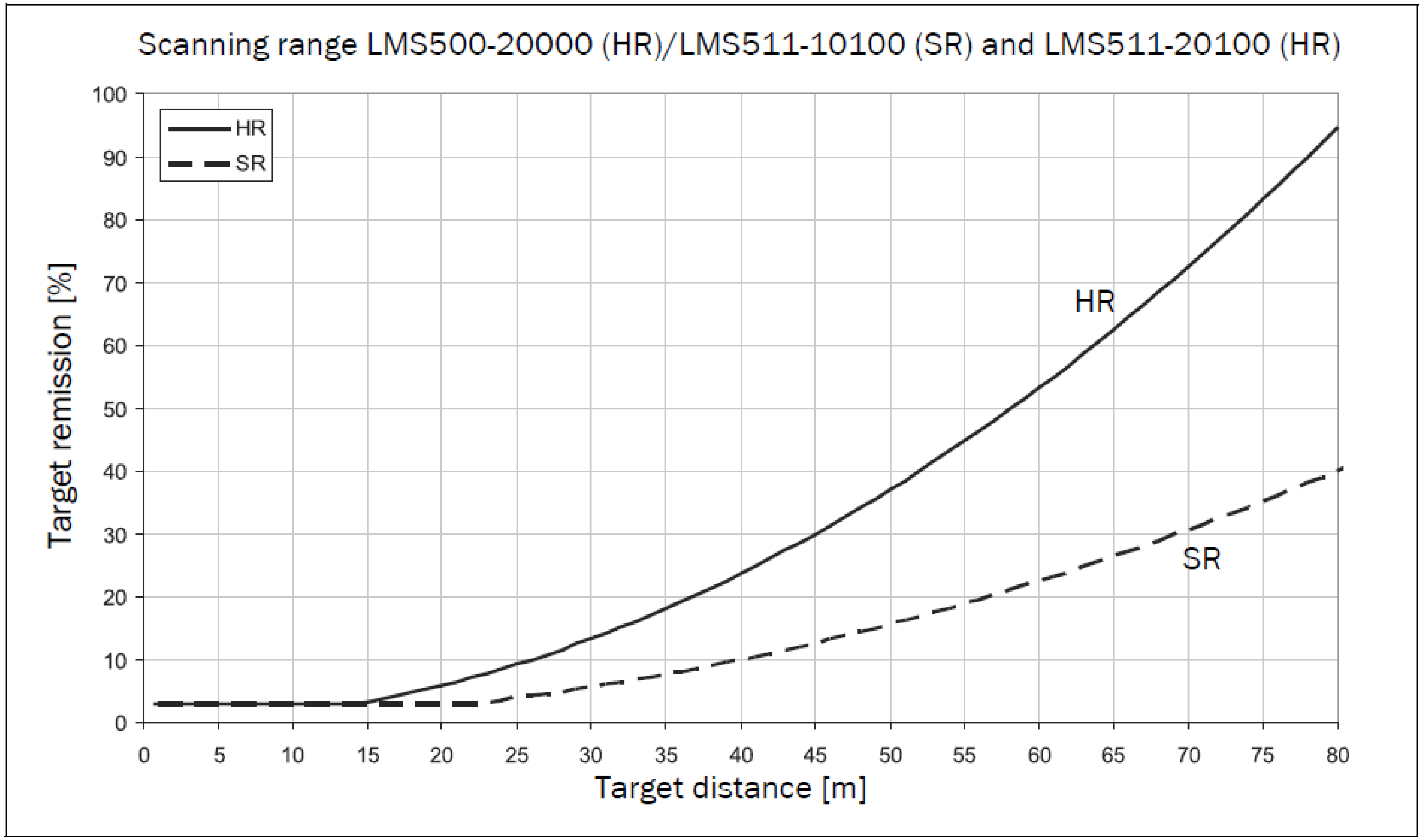
Detection Range?



..90% Remission? Range can depend on target and scenario.

Radar	SMS UMRR (type 29 antenna model)	SMS UMRR (type 30 antenna model)	SMS UMRR (type 31 antenna model)	Delphi ESR Long Range	Delphi ESR Middle Range	Bosch Mid-Range Radar	Bosch Long-Range Radar (LRR3)	ARS 3XX Radar (Continental)	SRR 2XX Radar (Continental)
Mnimum and maximum range	1 to 160 m	1 to 90 m	1 to 45 m	1 to 174 m	1 to 60 m	1 to 160 m (front); 1 to 100 m (rear)	0,5 to 250 m	0,25 to 200 m	1 to 50 m
Lidar	ibeo LUX	ibeo LUX HD	ibeo LUX 8L	ibeo minI LUX	SRL 1 Lidar Continental	UTM-30LX/EW Hokuyo	UXM-30LX-EW Hokuyo	UXM-30LXH-EWA Hokuyo	LD-MRS Series Sick
Distance range	200 m (average)	90 m (@ 90% remission)	200 m	40 m	10.0 m (13.5 m expanded distance)	30 m	30 m	0.1 to 80m @ 90% remission	0.02 -5.6 m

AV Sensor-Set Detection Range

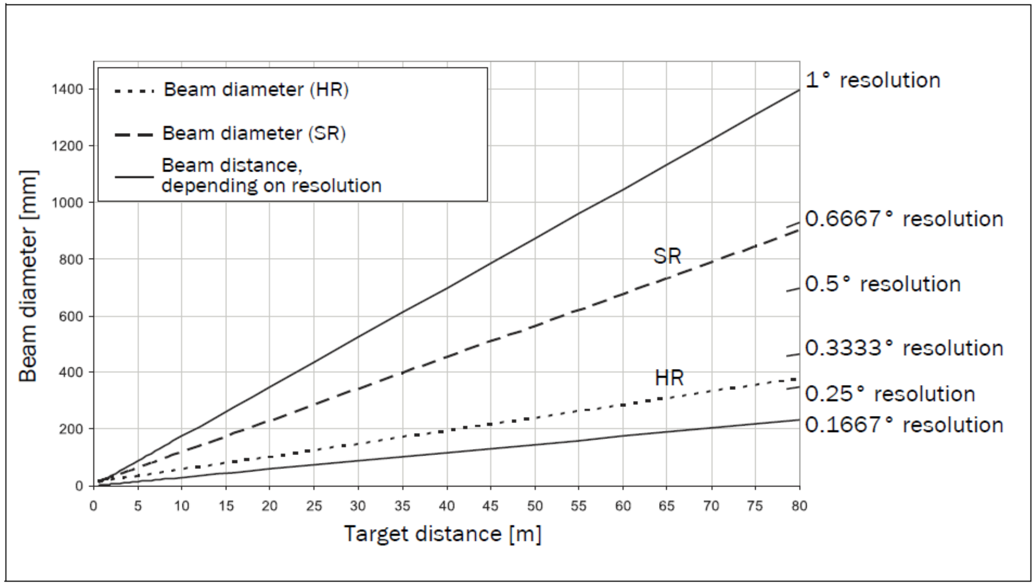


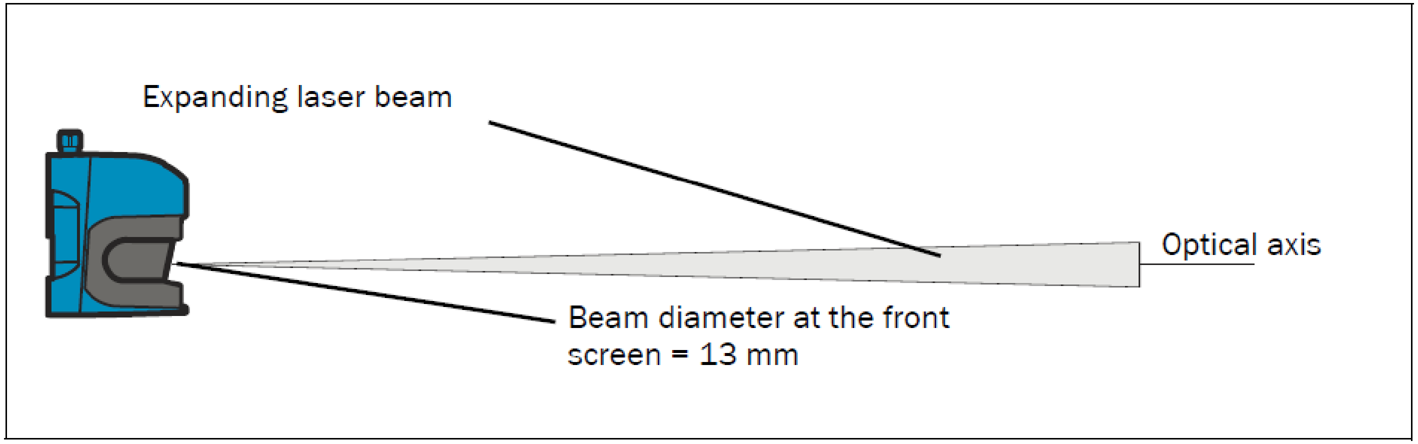
Example of how detection range depends on target remission for a LMS5xx Laser Measurement Sensors – Sick, 2015

AV Sensor-Set Detection Range

Errors often result from false assumption.

Example: Falsely assuming that a LIDAR beam is a “dot”.





LMS5xx Laser Measurement Sensors – Sick, 2015

AV Sensor-Set Weather Impact

AV Sensor-Set Lidar Multi-Echo Technology

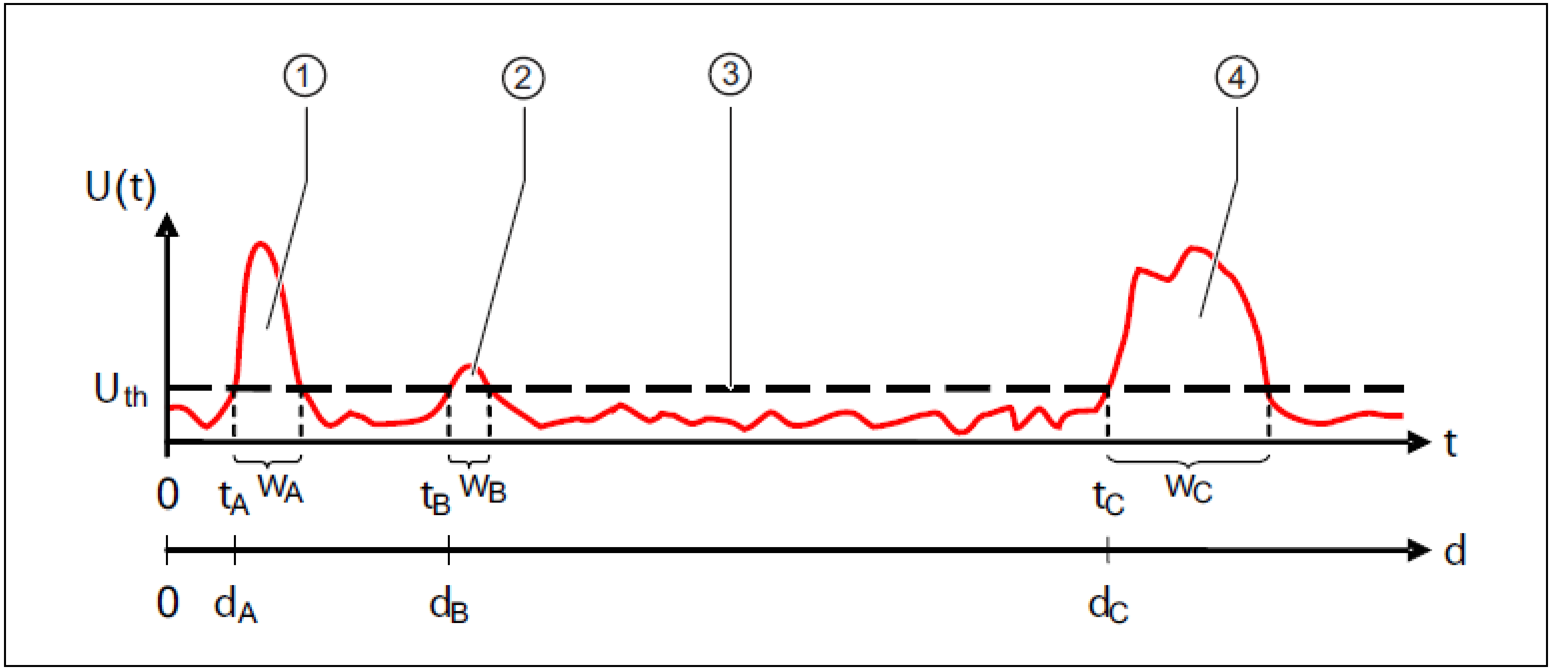


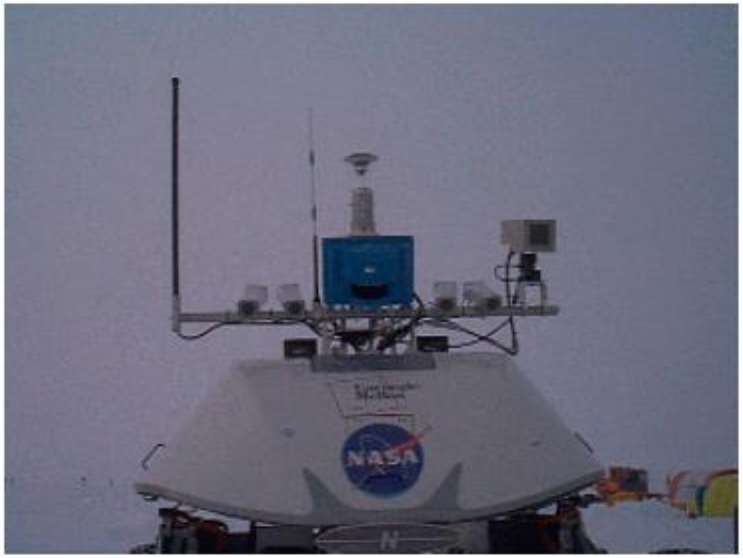
Abb. 3-3: Multi-Echo-Fähigkeit

Legende:

① Beispiel Echo Glasscheibe
② Beispiel Echo Regentropfen
③ Schwellenspannung
④ Beispiel Echo Gegenstand

1) Glas
2) Rain drop
3) Noise
4) Vehicle

AV Sensor-Set Lidar Multi-Echo Technology



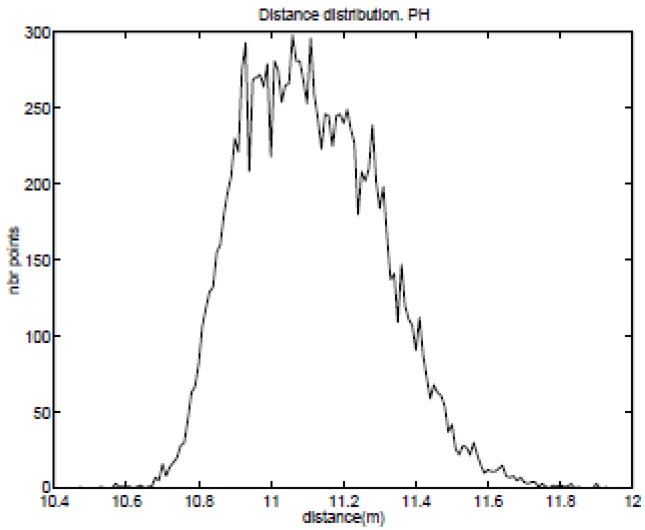
Characteristics	Riegl laser LD-3100HS	SICK laser LMS-220
Type	telemeter	laser stripe
Wavelength	900±100 nm	920 nm
Beam divergence	3 mrad max.	7 mrad
Information recorded	Distance (12 bits) Energy returned (8 bits) Temperature	Distance (13 bits)
Theoretical range	50 to 150 m	50 m
Accuracy (mean value)	±20mm	±20mm in single scan mode
Operation Temperature	$-30..+50°C$	$-30..+70°C$

Table 3. Laser characteristics

Preliminary Results on the use of
Stereo, Color Cameras and Laser Sensors in Antarctica
Nicolas Vandapel, Stewart J. Moorehead, William Whittaker, 2000

AV Sensor-Set Lidar Multi-Echo Technology

Target at 11m, moderate snow, increased standard deviation



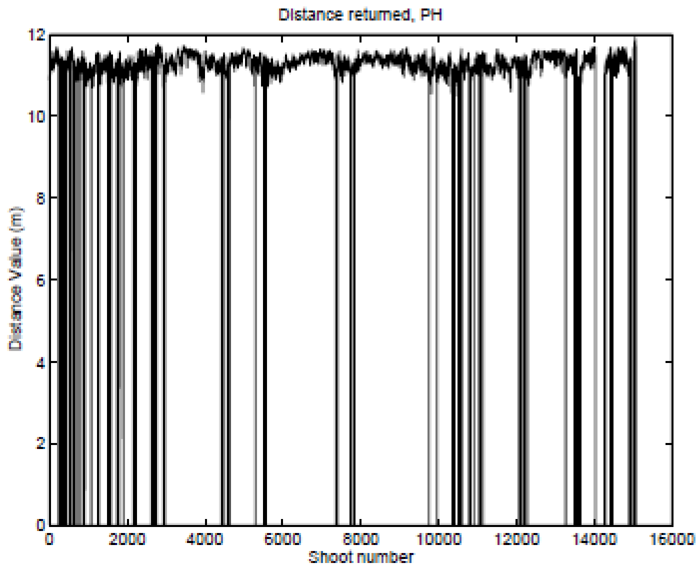
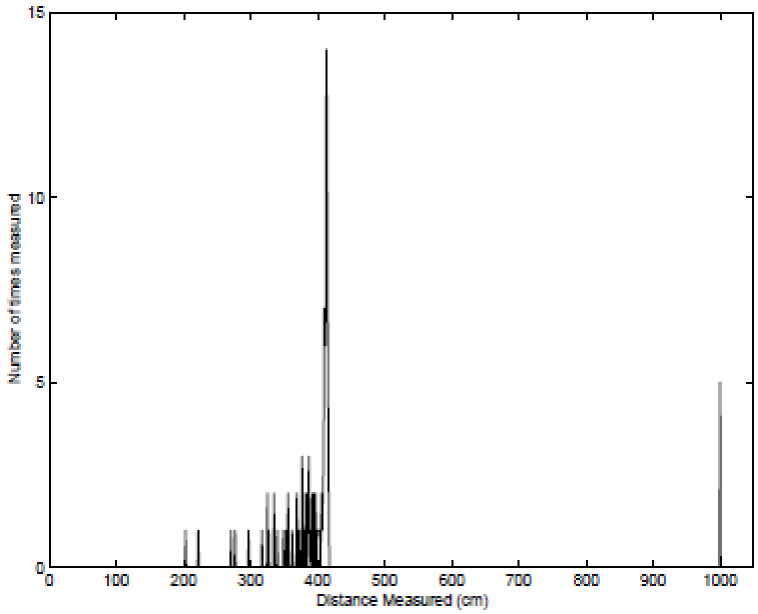


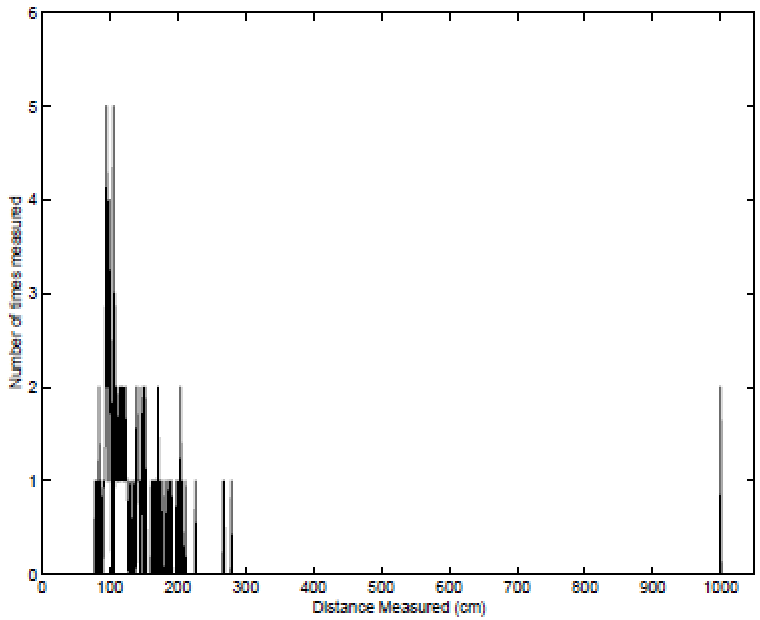
Figure 11. Distance Distribution

Preliminary Results on the use of
Stereo, Color Cameras and Laser
Sensors in Antarctica
Nicolas Vandapel, Stewart J.
Moorehead, William Whittaker, 2000

AV Sensor-Set Lidar Multi-Echo Technology

Moderate(left) and heavy snow(right), target at 4m





Preliminary Results on the use of
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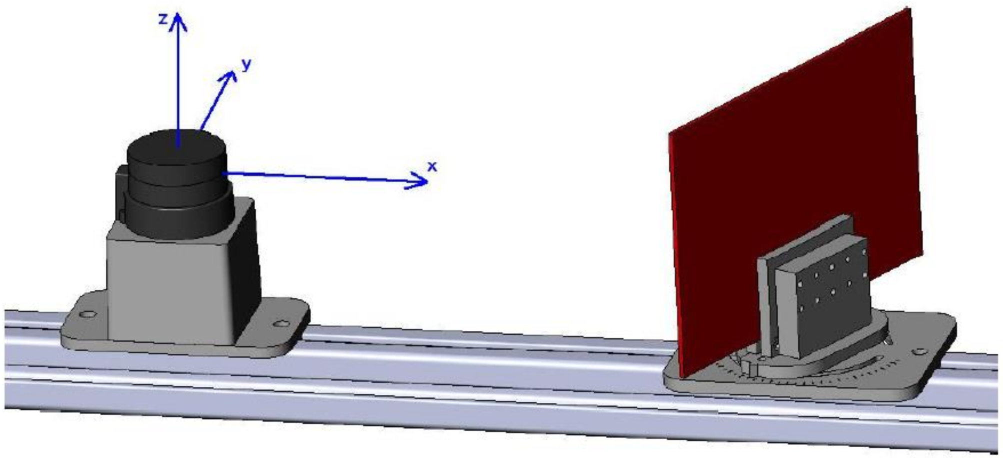
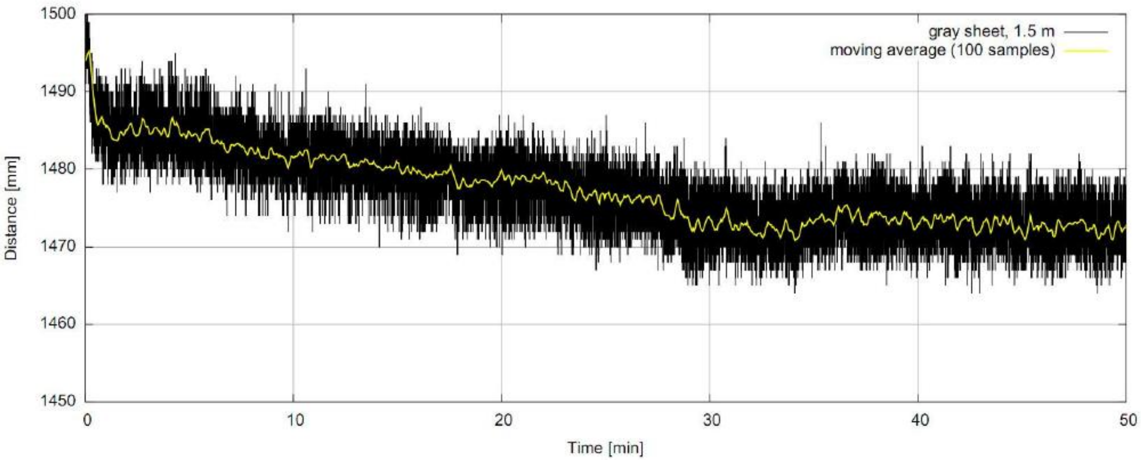
Moorehead, William Whittaker, 2000

Exemplary scenario sensor performance impacts

Measured Distance (Lidar):



Measured distance over time (heat dissipation of the sensor)

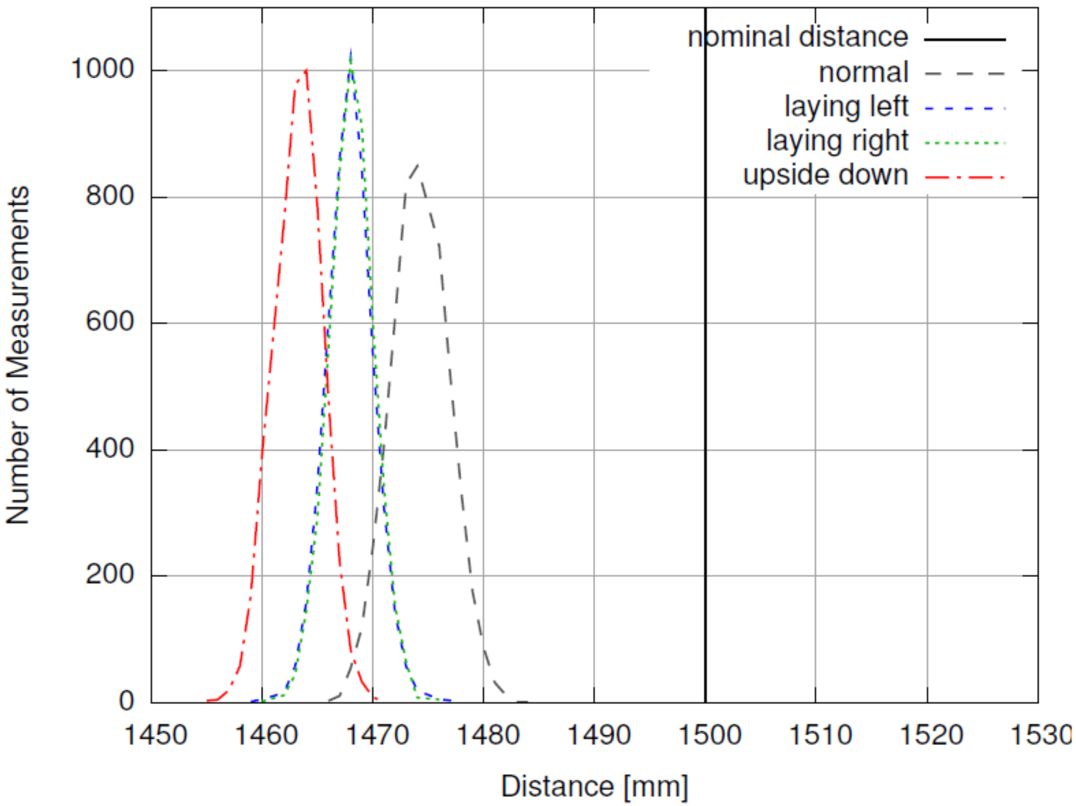


Laurent Kneip, Fabien Tˆache, Gilles Caprari, and Roland Siegwart, "*Characterization of the compact Hokuyo URG-04LX 2D laser range Scanner*", IEEE International Conference on Robotics and Automation, 2009

Exemplary scenario sensor performance impacts

Measured Distance (Lidar):

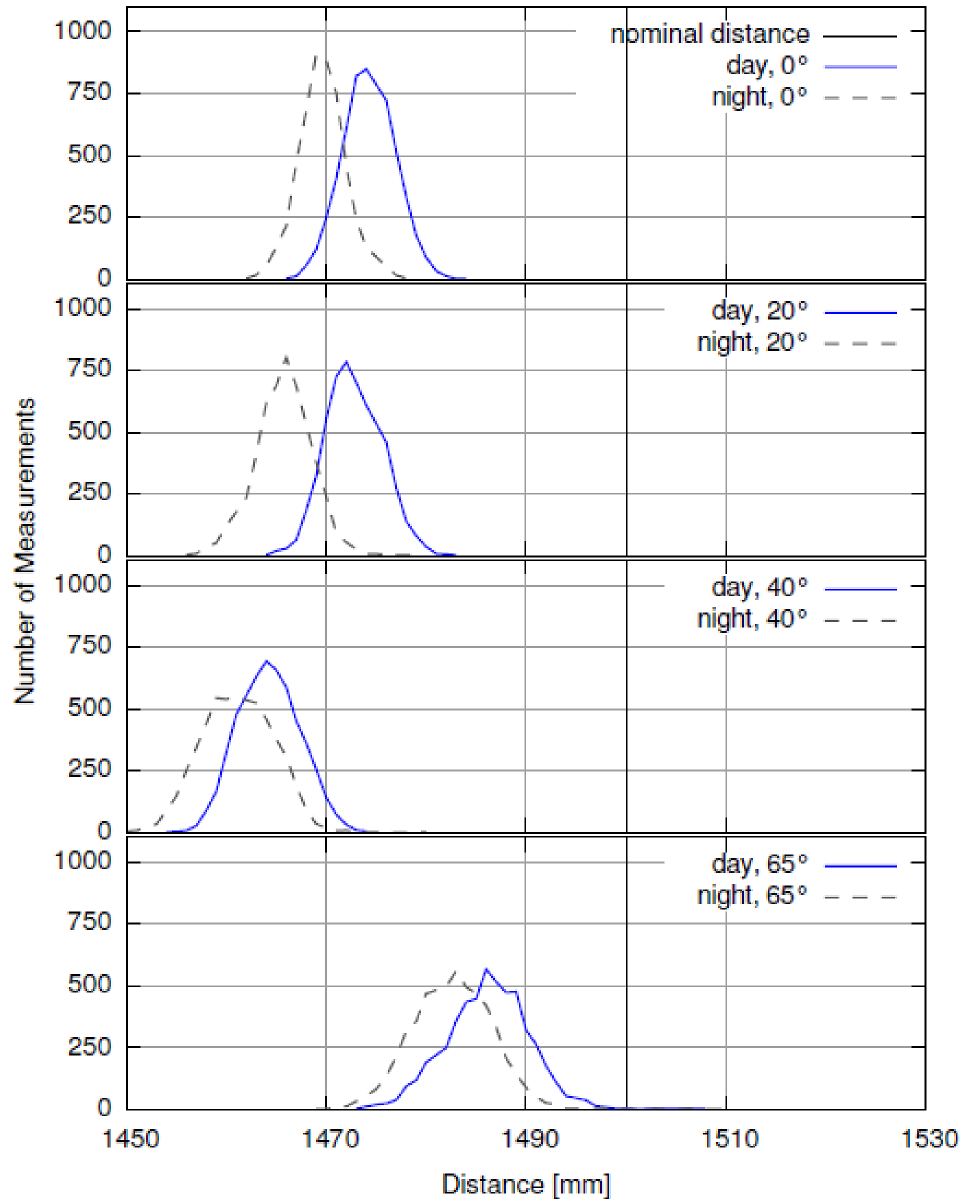
Measured distance and sensor orientation?



Laurent Kneip, Fabien Tˆache, Gilles Caprari, and Roland Siegwart, *"Characterization of the compact Hokuyo URG-04LX 2D laser range Scanner"*, IEEE International Conference on Robotics and Automation, 2009

Exemplary scenario

Measured Distance (Lidar):

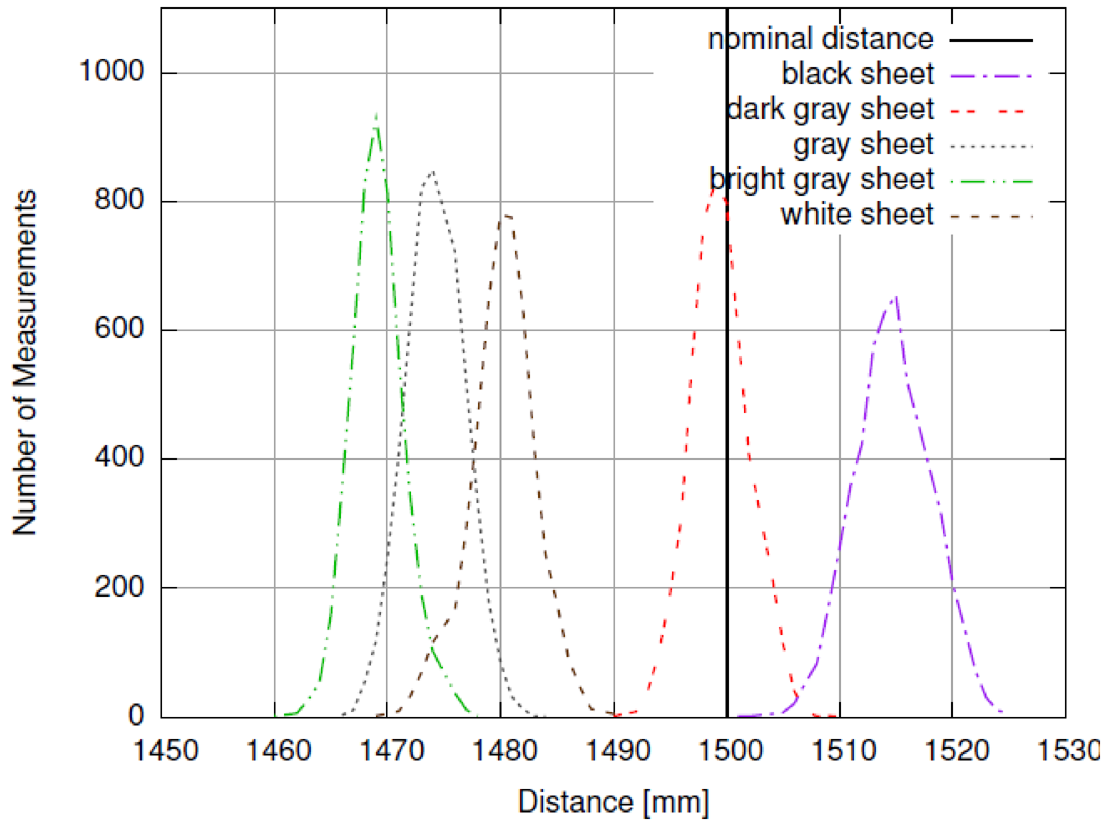


Measured distance, day or night?

Laurent Kneip, Fabien Tˆache, Gilles Caprari, and Roland Siegwart, *"Characterization of the compact Hokuyo URG-04LX 2D laser range Scanner"*, IEEE International Conference on Robotics and Automation, 2009

Exemplary scenario sensor performance impacts

Measured Distance (Lidar):

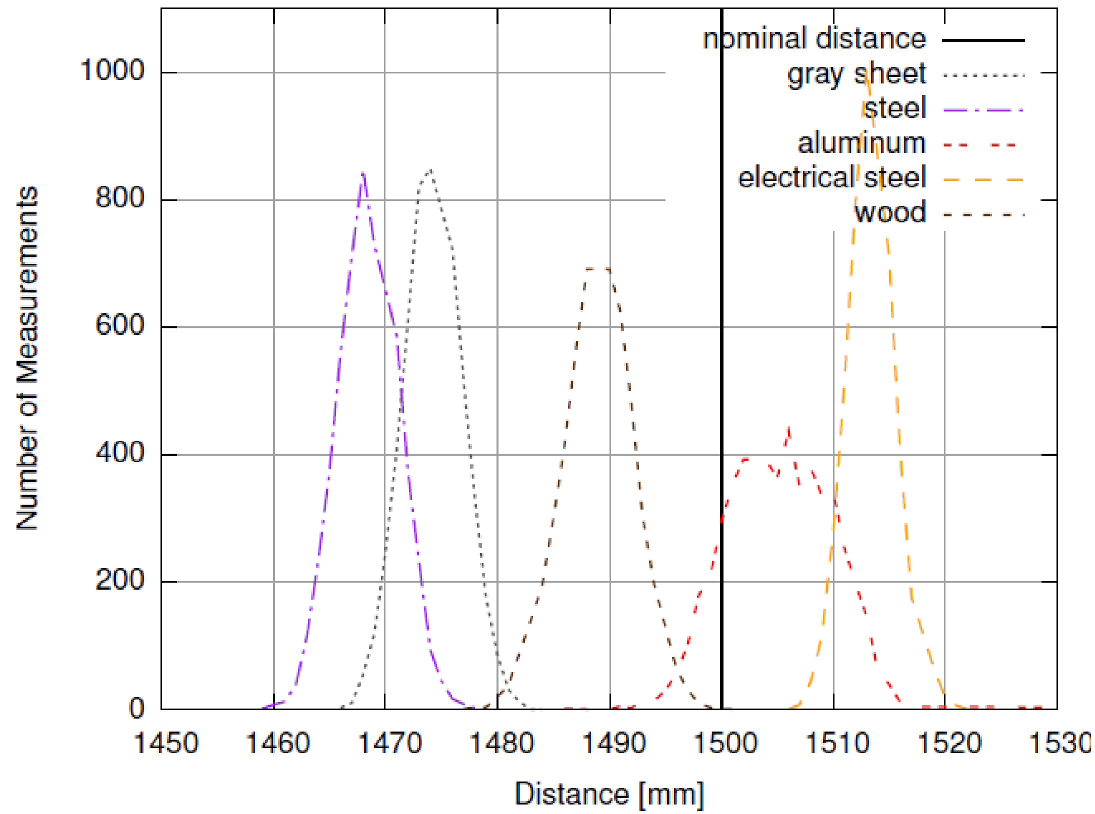


Measured distance and surface brightness or color?

Laurent Kneip, Fabien Tˆache, Gilles Caprari, and Roland Siegwart, “*Characterization of the compact Hokuyo URG-04LX 2D laser range Scanner*“, IEEE International Conference on Robotics and Automation, 2009

Exemplary scenario sensor performance impacts

Measured Distance (Lidar):

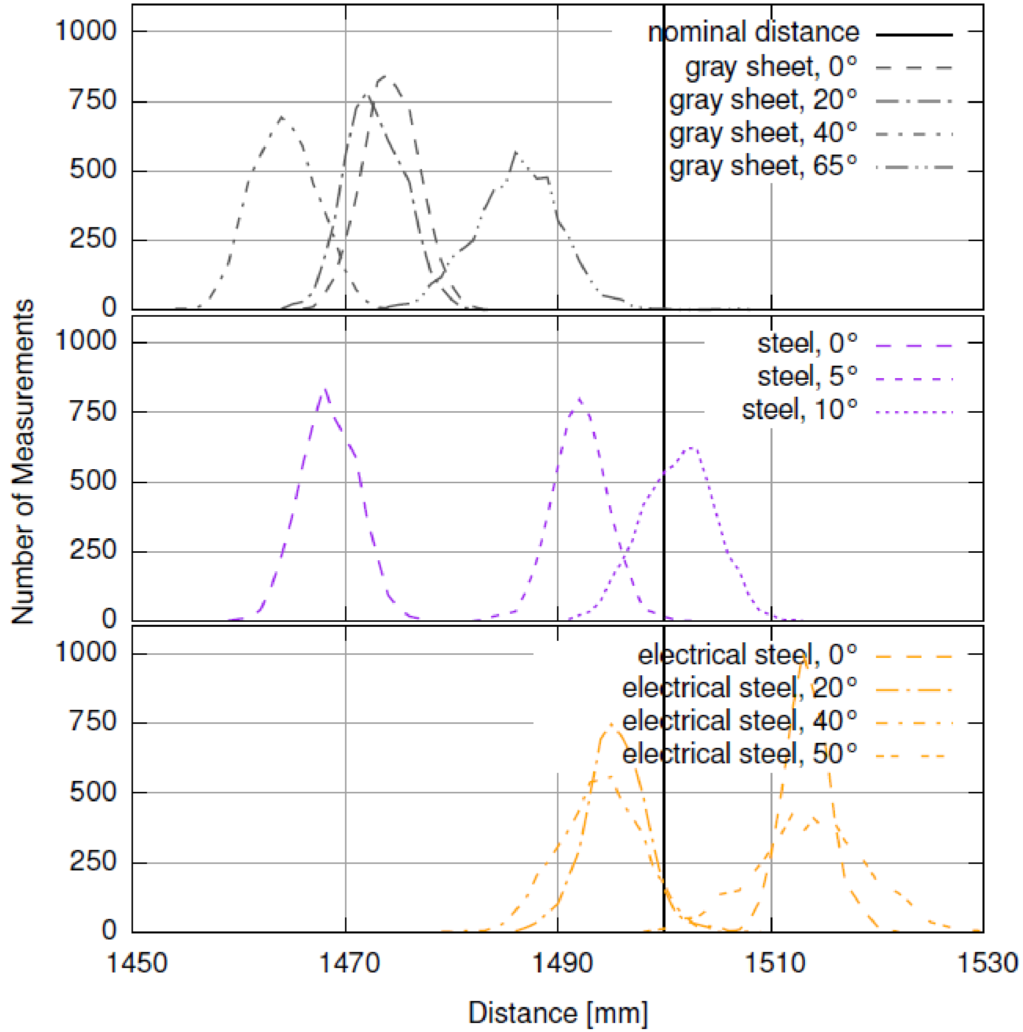


Measured distance and target material?

Laurent Kneip, Fabien Tˆache, Gilles Caprari, and Roland Siegwart, *“Characterization of the compact Hokuyo URG-04LX 2D laser range Scanner“*, IEEE International Conference on Robotics and Automation, 2009

Exemplary scenario sensor performance impacts

Measured Distance (Lidar):



Measured distance and incident angle?

Laurent Kneip, Fabien Tˆache, Gilles Caprari, and Roland Siegwart, “*Characterization of the compact Hokuyo URG-04LX 2D laser range Scanner*“, IEEE International Conference on Robotics and Automation, 2009

Tesla Autopilot tried to kill me!

RockTreeStar

Subscribe 60

1,347,405

28
D

Light rain, failing to stay on road + failed curve prediction

Accidentaly exiting highway, failure to understand road exit

Leaves on curbstone, failing to follow curve

Widening of road, failure to understand and follow road

Failure to detect small traffic cones on the road / failure to stop timely in front of cones

Failure to timely stop in front of barrier

Road contrast light/dark patch, strong curve

Fog/Steam and manhole cover – two sources of false positives

Lack of camera features

Pot holes filled with water are difficult to detect

Another smoke scenario

Water spray can limit surrounding sensor performance

Crocodiles everywhere!

Sun exposure – Blindness. IR Comparison.

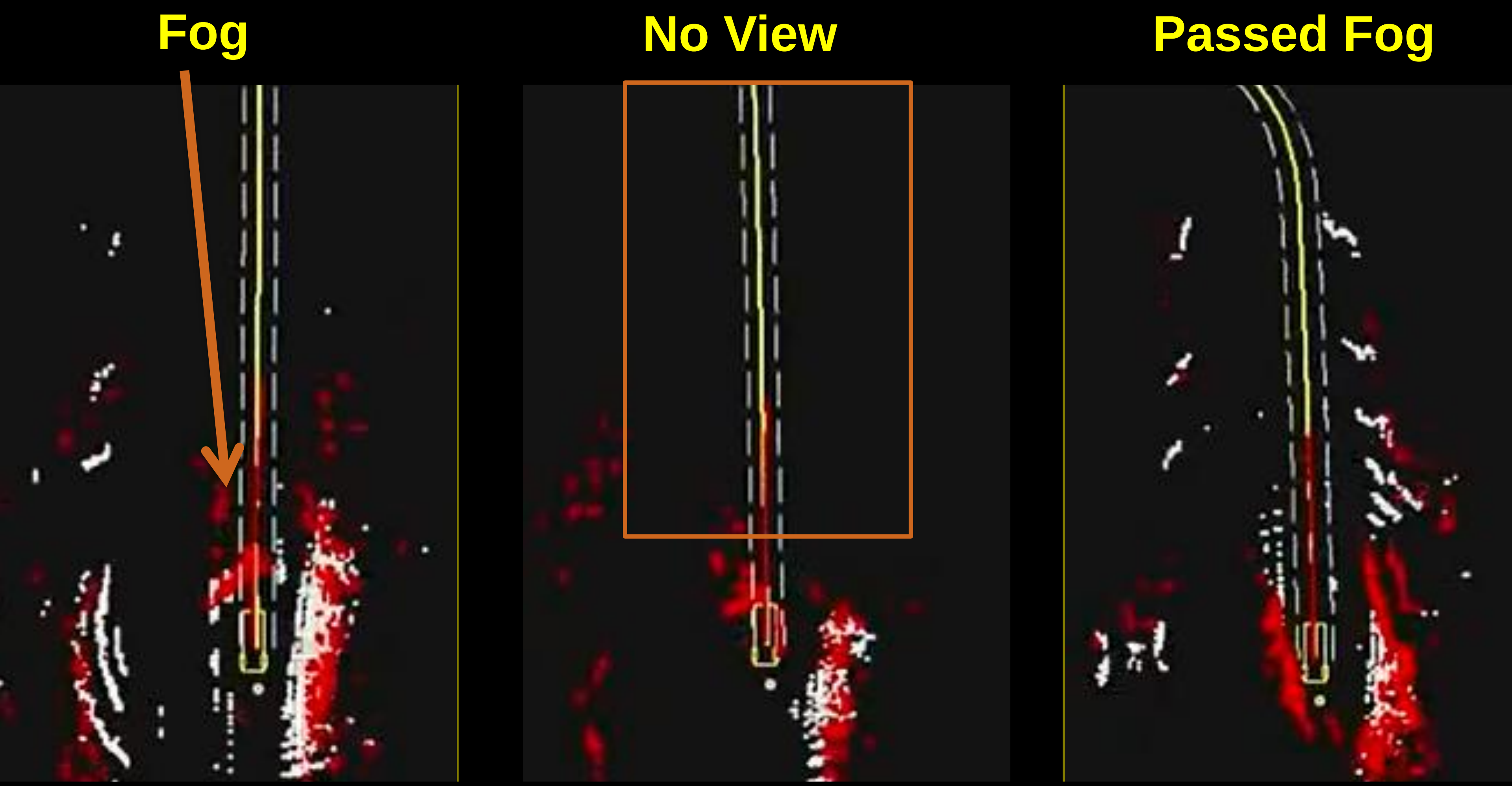
Robotics & Embedded Systems

Optical variations. Apperance example speed bumps

Example of fog detection distance reduction

Example of fog detection distance reduction

Example of fog detection distance reduction



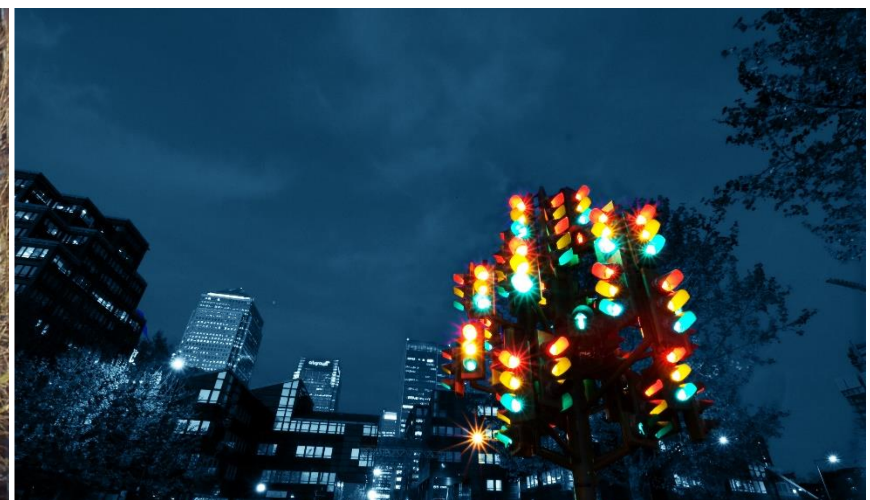
Fog impact on sensor performance

Snow on the ground

- Bycicle driver may fall to ground
- Traffic lights are barely visible
- Dirt on sensors can reduce their performance
- Lanes are hidden
- …

Art as a risk.

- "Traffic Light Tree is a public sculpture in London, England, created by the French sculptor Pierre Vivant following a competition run by the Public Art Commissions Agency. **Originally situated on a roundabout near Canary Wharf**, at the junction of Heron Quay, Marsh Wall and Westferry Road, it is now located on a different roundabout, near Billingsgate Market."



Traffic light tree was relocated… if it would have been included in backend maps, the map would have needed to be updated

SONNENSTRAHLEN

Fassade der Freiburger UB blendet zu sehr – Banner müssen aufgehängt werden

Im Frühjahr und Herbst wird die Hi-Tech-Fassade der Freiburger Uni-Bibliothek an der Südostseite verhüllt werden müssen. Der Grund: Steht die Sonne tief, spiegelt sie sich so heftig in der Fassade, dass Autofahrer geblendet werden.

Badische Zeitung
Suchbegriff
bz-ticket.de TIPPS-TERMINE-TICKETS
Freitag, 22. Januar 2016
START | LOKALES | NACHRICHTEN | SPORT | MEINUNG | FREIZEIT | RATGEBE
Freiburg | Breisgau | Emmendingen | Ortenau | Schwarzwald | Lörrach & Dreiland | Waldsh

INNENSTADT

Fassade blendet wieder: XXL-Banner an der Unibibiothek

Es ist ein Anblick, an den man sich erst wieder gewöhnen muss: Ein riesiges schwarzes Banner verdeckt die Fassade der neuen Freiburg Universitätsbibliothek. Sie würde sonst Autofahrer blenden.

SONNENSTRAHLEN

Fassade der Freiburger UB blendet zu sehr – Banner müssen aufgehängt werden

Im Frühjahr und Herbst wird die Hi-Tech-Fassade der Freiburger Uni-Bibliothek an der Südostseite verhüllt werden müssen. Der Grund: Steht die Sonne tief, spiegelt sie sich so heftig in der Fassade, dass Autofahrer geblendet werden.

Badische Zeitung
Suchbegriff
bz-ticket.de
TIPPS-TERMINE-TICKETS
Freitag, 22. Januar 2016
START | LOKALES | NACHRICHTEN | SPORT | MEINUNG | FREIZEIT | RATGEBE
Freiburg | Breisgau | Emmendingen | Ortenau | Schwarzwald | Lörrach & Dreiland | Waldsh

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Only happens 2 times per year:

- 20 minutes per day
- approximately at 9 o'clock (autumn and spring)
- Blinding strong enough to cause temporary black spots for driver vision
- Difficult to find during random tests, but blinding is a known effect and can be tested

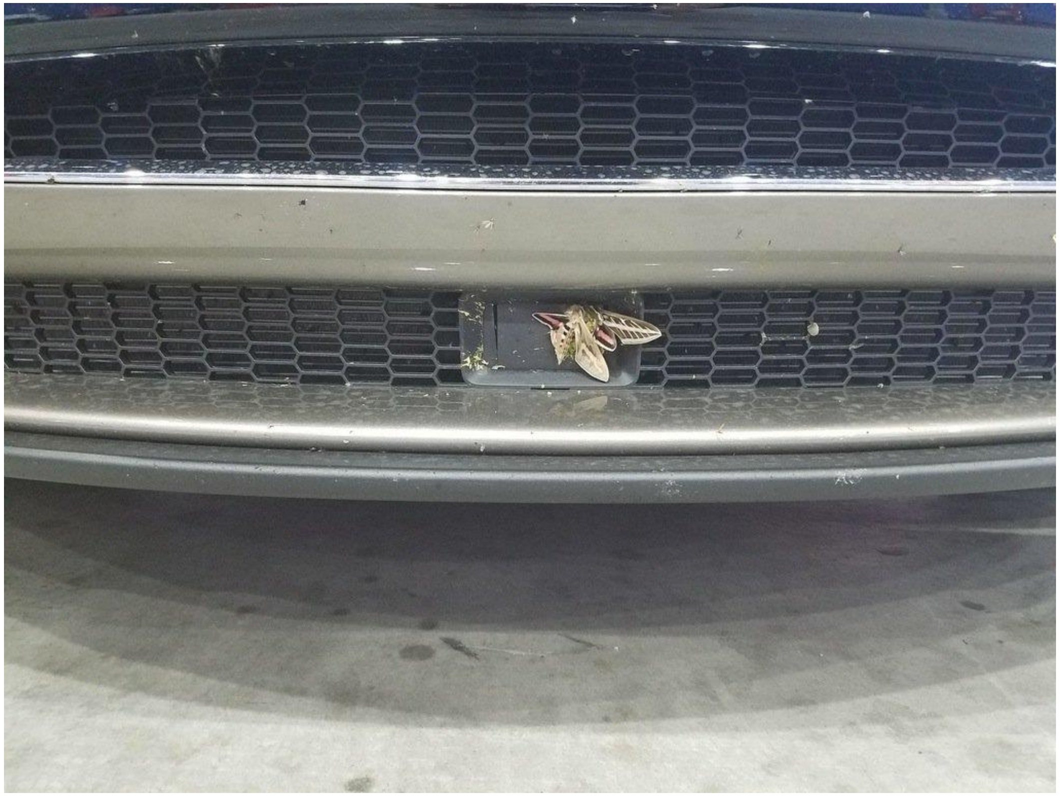
Detection of overhanging objects / cliffs

- Model S software supposedly crashes car. Tesla blames the driver?
- Overhanging objects are a challenge anyway.

http://ideas.4brad.com/files/tesla-crash.jpg

Sensor performance limited by insects / dirt

- Tesla knocked out by bug



http://www.techinsider.io/tesla-autopilot-knocked-out-by-moth-2016-5

More bugs.

- Traffic infrastructure can be fully covered by insects.

http://bilder.bild.de/fotos-skaliert/es-summt-und-brummt-als-die-bienen-sich-um-ihre-koenigin-scharen-und-dabei-leider-auch-die-ampel-bloc-44876528-40704156/2,w=650,c=0.bild.jpg

AV debugging

- Traffic infrastructure can be fully covered by insects.

http://bilder.bild.de/fotos-skaliert/der-imker-ist-da-mit-schutzkleidung-und-eimer-sammelt-er-die-bienen-ein--die-feuerwehr-hat-ihm-dafue-44880764-40706842/2,w=559,c=0.bild.jpg

„Following“ into false lanes due to loss of information

- False classification of cars, loss of lanes, challenges with following other cars
- Easy to accidentally switch lane and mess up logic.

https://www.youtube.com/watch?v=lTtLGP4cRaQ

AV Sensor-Set performance impact on comfort

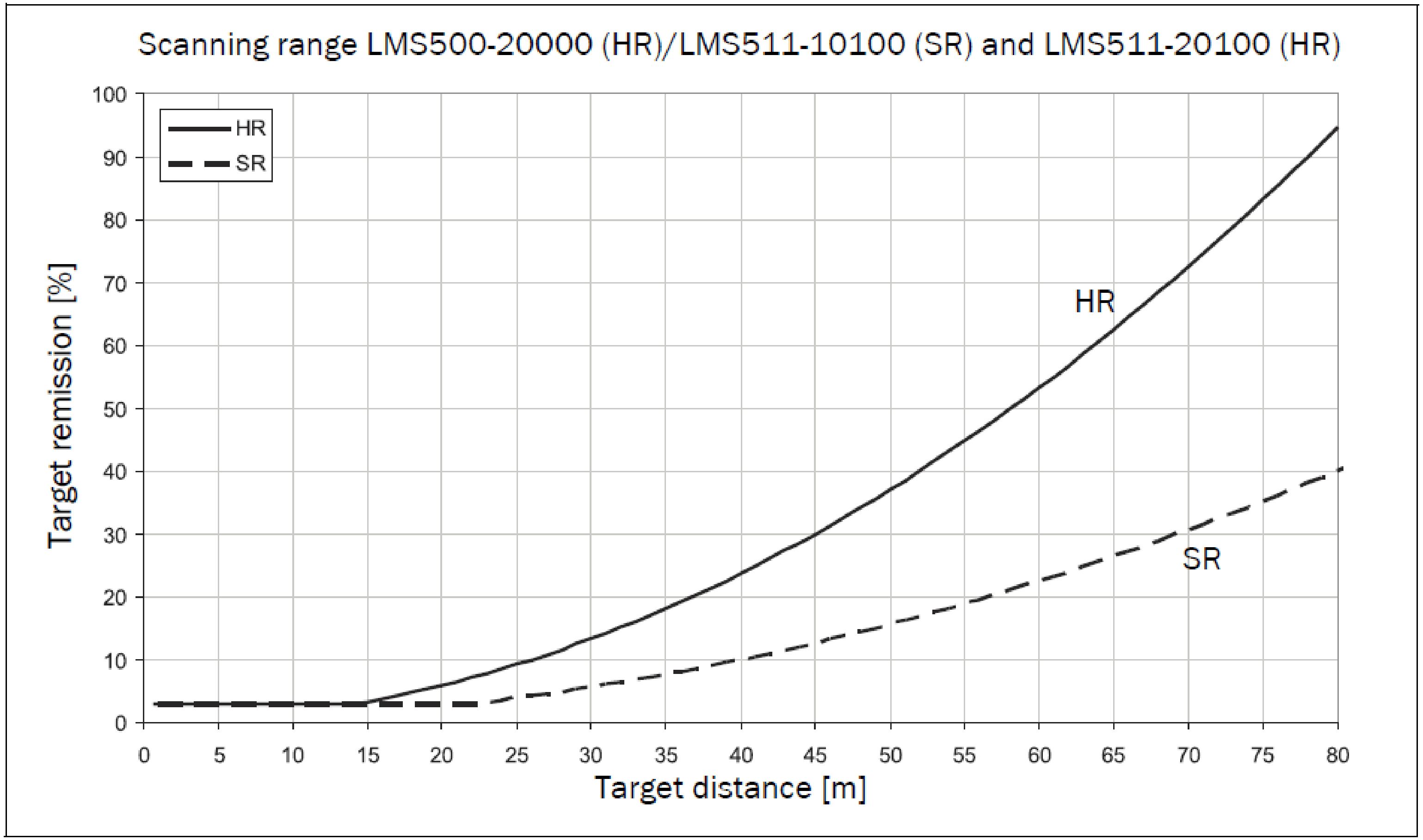
- “(With the Mercedes), during our test, in stop and go traffic, **it felt like we were a drunk drivers**. The vehicle ahead of us was either in a real hurry or on his phone and was weaving all over the lane crossing lines on both sides. The Mercedes followed him, as it should based on how the programming works. When a normal driver was in front of us**, the Mercedes would meander from one side of the lane to the other like a pinball**. If there was a crown in the road, the car would pull to the same side until it reached the road marking, correct and then meander to the same side again. **I can’t say it is confidence building.**”

Cause	Sep 2014	Oct 2014	Nov 2014	Dec 2014	Jan 2015	Feb 2015	Mar 2015	Apr 2015	May 2015	Jun 2015	Jul 2015	Aug 2015	Sep 2015	Oct 2015	Nov 2015	Total
disengage for weather conditions during testing	0	0	0	0	1	5	0	6	0	0	0	0	0	0	1	**13**
disengage for a recklessly behaving road user	1	0	1	1	1	3	3	7	0	0	0	2	1	0	3	**23**
disengage for hardware discrepancy	0	1	0	0	2	1	0	1	0	5	8	1	8	8	4	**39**
disengage for unwanted maneuver of the vehicle	0	3	6	14	15	1	3	2	1	0	3	2	0	3	2	**55**
disengage for a perception discrepancy	1	2	3	18	19	2	20	30	4	4	8	0	4	3	1	**119**
disengage for incorrect behavior prediction of other traffic participants	0	2	2	0	1	0	2	0	0	0	0	0	0	1	0	**8**
disengage for a software discrepancy	0	11	9	9	14	2	1	5	8	2	9	2	3	1	4	**80**
disengage for construction zone during testing	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0	**3**
disengage for emergency vehicle during testing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**1**
Total	**2**	**19**	**21**	**43**	**53**	**14**	**30**	**51**	**13**	**11**	**29**	**7**	**16**	**16**	**16**	**341**

- Large variety of error sources

Google disengagement report 2015, https://static.googleusercontent.com/media/www.google.com/en//selfdrivingcar/files/reports/report-annual-15.pdf

AV Sensor-Set Detection Range



Example of how detection range depends on target remission for a LMS5xx Laser Measurement Sensors – Sick, 2015

Lidar Simulation

- Lidar Range Measurement:
  - $R = ct/2$
  - R: Range; c: Lightspeed; t: time;
- Lidar Angular Measurement:
  - Sharply limited beam, which only illuminates limited area; measure outgoing angle

Extended simulation base material source:
Influences of weather phenomena on automotive laser radar systems. R. H. Rasshofer1, M. Spies2, and H. Spies. BMW & Spies
https://www.adv-radio-sci.net/9/49/2011/ars-9-49-2011.pdf

Lidar Simulation – Lidar Range Equation

- Lidar Range Equation for non-elastic scattering, as convolution between transmit signal Pt and spatial impulse response H(R):

$$P_{\mathrm{R}}(R) = C_A \int_{t'=0}^{2R/c} P_{\mathrm{T}}(t')\ H(R - ct'/2)dt'$$

- Pr(R): Received Power as function of target range
- System constant C_A: $C_A = c\eta A_{\mathrm{R}}/2$
- Ar: Aperture Area of optical receiver
- η : Losses in receiver optic

Lidar Simulation – Transmit Pulse Modeling

- Dirac-shaped transmit pulse with total pulse energy Ep:

$$P_{\mathrm{T}\delta}(t) = E_{\mathrm{P}}\,\delta(t)$$

- Integrated into Lidar Range Equation:

$$\begin{aligned} P_{\mathrm{R}\delta}(R) &= C_A \int_{t'=0}^{2R/c} E_{\mathrm{P}}\,\delta(t')\; H(R - ct'/2)\,dt' \\ &= C_A E_{\mathrm{P}} H(R). \end{aligned}$$

- Only valid for R>>cτ, with τ: duration of transmit pulse (typically 10 to 20 ns) (cτ typically 3m to 6m)

Lidar Simulation – Transmit Pulse Modeling

- More realistic pulse model to improve applicable range:

$$P_{\mathrm{T}}(t) = \begin{cases} P_0 \sin^2\left(\frac{\pi}{2\tau_H}\, t\right) & 0 \leq t \leq 2\tau_H \\ 0 & \text{else} \end{cases}$$

- P_0: Peak power of laser pulse
- τ_H: half-power pulse width
- Resulting in total energy:

$$E_{\mathrm{P}} = P_0 \tau_{\mathrm{H}}$$

- Typically P_0 up to 80W

Lidar Simulation – Spatial Impulse Response Function

- Spatial Impulse Responses of optical channel H_C and spatial impulse response of target H_T: H=H_C*H_T, with:

$$H_C(R) = \frac{T^2(R)}{R^2}\xi(R)$$

- T(R): Total one-way transmission loss in transmission medium

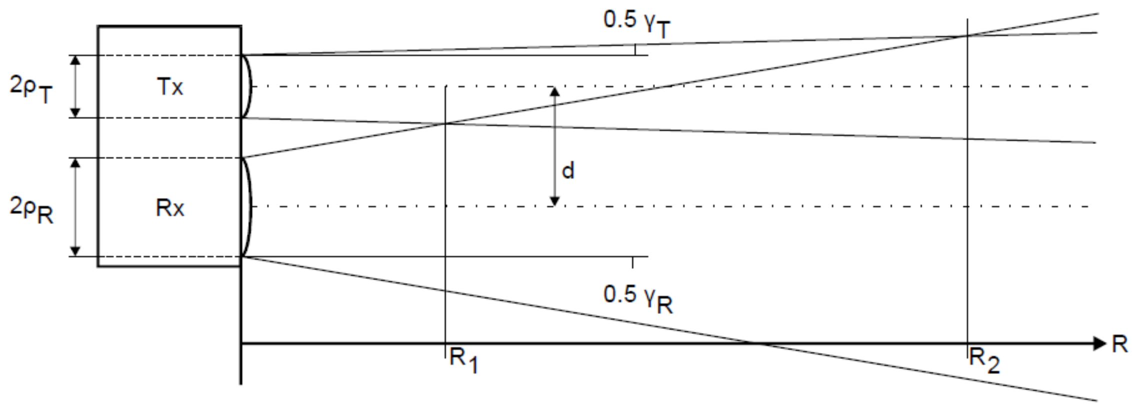
$$T(R) = \exp\left(-\int_{r=0}^{R} \alpha(r)dr\right)$$

- α(R): Local extinction coefficient
- ξ(R): Crossover function

Lidar Simulation – Crossover function

- ξ(R): Crossover function as ratio between area A_T illuminated by transmitter and area A_R observed by receiver

$$\xi(R) = \begin{cases} \frac{A_R(R) \cap A_T(R)}{A_T(R)} & \text{if } A_R(R) \cap A_T(R) < A_T(R) \\ 1 & \text{else.} \end{cases}$$



- Depends on sensor type. Constant for coaxial transmit/receive optics.

Lidar Simulation – Crossover function

- For bistatic beam configuration using circular illumination and detection areas with parallel optical axis and displacement d, R_1 of first contact between transmit and reception is given by:

$$R_1 = \frac{d - \rho_T - \rho_R}{\tan(\gamma_T/2) + \tan(\gamma_R/2)}$$

$$R_2 = \frac{d - \rho_R + \rho_T}{\tan(\gamma_R/2) - \tan(\gamma_T/2)}$$

- ρ_T, ρ_R: aperture radius
- γ_T, γ_R: Opening angle

Lidar Simulation – Crossover function

- Defining:

$$r_\mathrm{T} = R\tan(\gamma_\mathrm{T}/2) + \rho_\mathrm{T}$$

$$\phi_\mathrm{T} = 2\arccos\left(\frac{r_\mathrm{T}^2 - r_\mathrm{R}^2 + d^2}{2d\,r_\mathrm{T}}\right)$$

$$r_\mathrm{R} = R\tan(\gamma_\mathrm{R}/2) + \rho_\mathrm{R}$$

$$\phi_\mathrm{R} = 2\arccos\left(\frac{r_\mathrm{R}^2 - r_\mathrm{T}^2 + d^2}{2d\,r_\mathrm{R}}\right)$$

- Gives the crossover function:

$$\xi(R) = \begin{cases} 0 & \text{if } R \le R_1 \\ \dfrac{r_\mathrm{T}^2(\phi_\mathrm{T} - \sin\phi_\mathrm{T}) + r_\mathrm{R}^2(\phi_\mathrm{R} - \sin\phi_\mathrm{R})}{2\pi r_\mathrm{T}^2} & \text{if } R_1 < R < R_2 \\ 1 & \text{if } R \ge R_2 \end{cases}$$

Lidar Simulation – Spatial Impulse Response Function

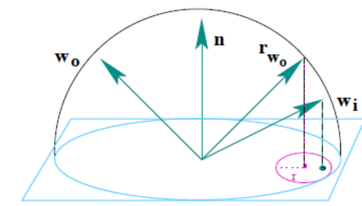
- For Laser Radar Pulses reflected at plain surfaces of solid objects that don't change the time signature of the laser pulse (hard targets) (target at R_0, with target area A_TA

$$H_{\mathrm{T}\delta}(R) = \begin{cases} \beta_0 \, \delta(R - R_0) & \text{if } A_{\mathrm{TA}} \geq A_{\mathrm{T}}(R_0) \\ \beta_0 \, \delta(R - R_0) \frac{A_{\mathrm{TA}}}{A_{\mathrm{T}}} & \text{if } A_{\mathrm{TA}} < A_{\mathrm{T}}(R_0) \end{cases}$$

- A_T(R0): Describes cross-section area of transmit beam at R0
- β_0: Differential reflectivity of target. Simple Lambert reflection model based on reflectivity from 0 to 1:

$$\beta_0 = \Gamma / \pi \, .$$

Lidar Simulation – Target Reflectivity; BRDF



- Bidirectional Reflectance Distribution Function (BRDF)

- **Empirical Model:** Provide simple formulation to mimic specific kind of reflection. Low computational cost, adjustable by parameters, without consideration of physics.

- **Theoretical Model:** Accurately simulate light scattering by using physics laws. Complex expression. High computational effort.

- **Experimental Model:** Measure BRDF with gonioreflectometer varying light sources and sensor positions. Slow. Limited data. Limited resolution.

Lidar Simulation – Target Reflectivity; BRDF

- Bidirectional Reflectance Distribution Function (BRDF)

- **Physical-based Reflectance Models:**
  - Ideal reflection: light incoming from a given direction is reflected in a single direction following law of reflection.
  - Other models: Torrance-Sparrow BRDF Beard-Maxwell BRDF; Cook-Torrance BRDF; Kajiya BRDF; Poulin-Fournier BRDF; He-Torrance-Sillion-Greenberg BRDF…

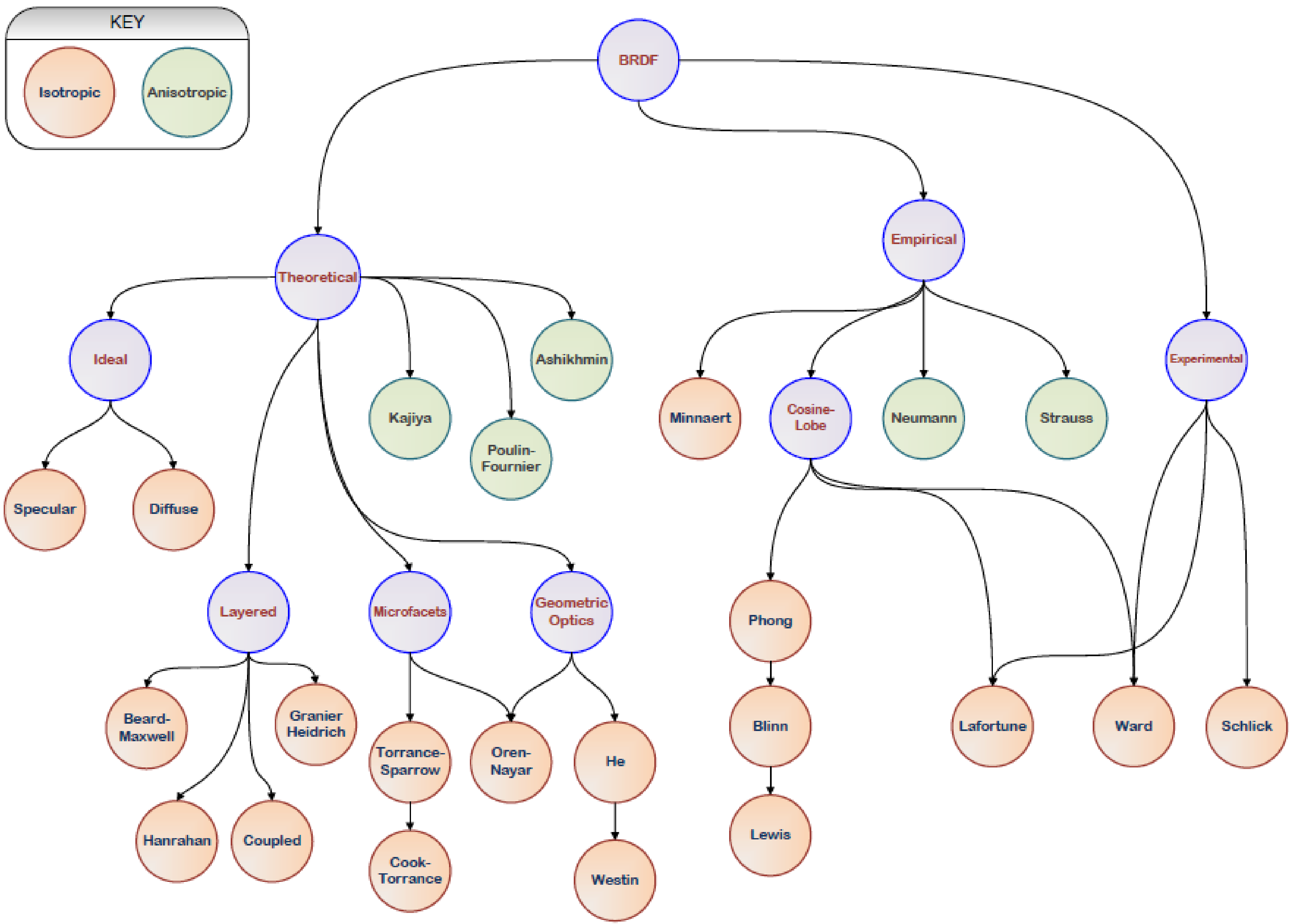
Lidar Simulation – Target Reflectivity; BRDF

- Bidirectional Reflectance Distribution Function (BRDF)

- **Empirical Models**
  - Phong BRDF; Blinn BRDF; Lewis BRDF; Neumann-Neumann BRDF; Strauss BRDF…

- **Experimental models Models**
  - Ward BRDF, Schlick BRDF, Lafortune BRDF..

Lidar Simulation – Target Reflectivity; BRDF

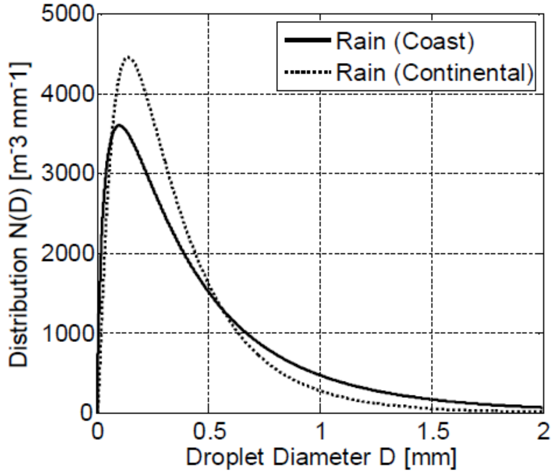


Robotics & Embedded Systems

Lidar Simulation – Influence of rain and fog

- Extiction coefficient:

$$\alpha = \frac{\pi}{8} \int_{D=0}^{\infty} D^2 Q_{\mathrm{EXT}}(D) N(D) dD$$

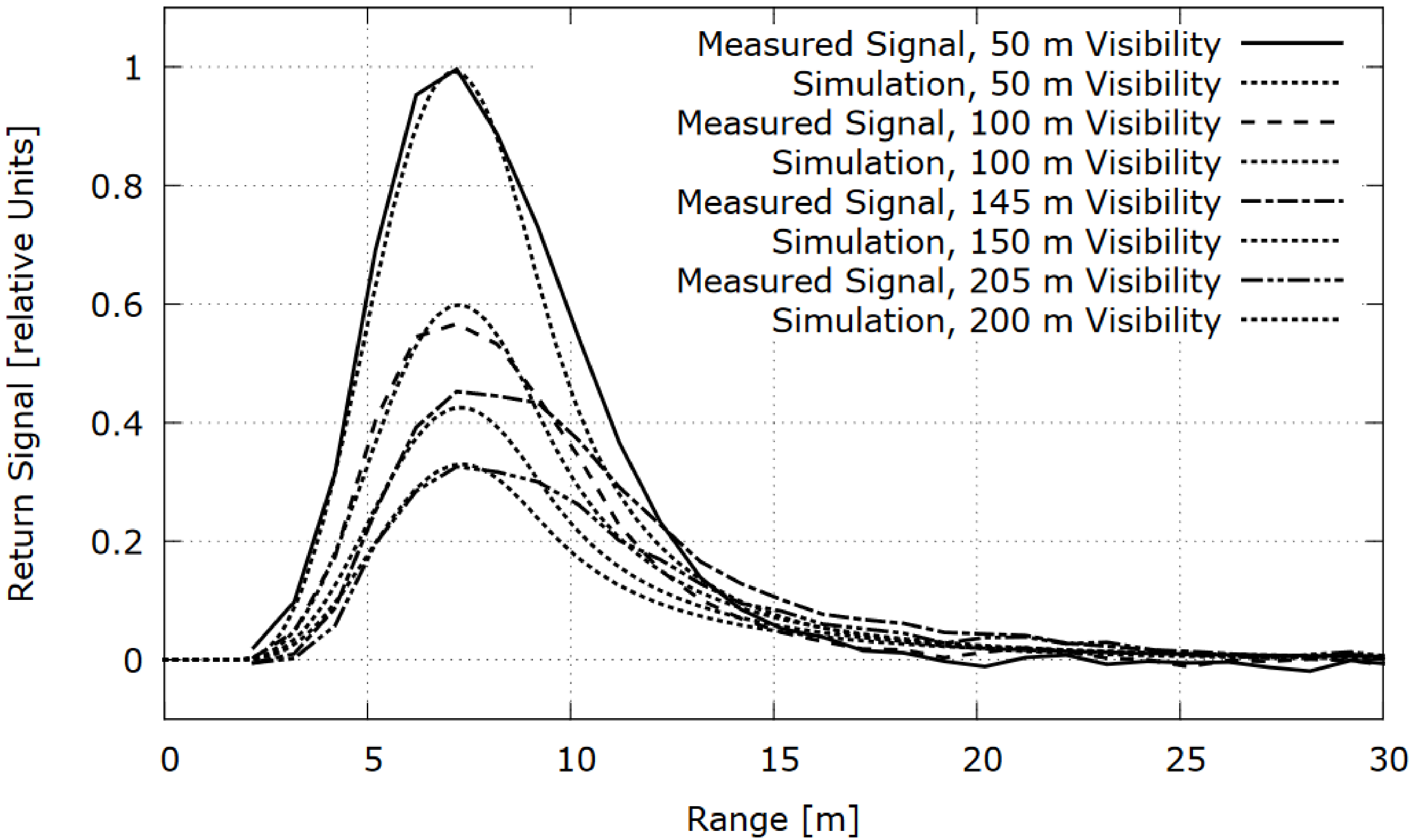


- Q_EXT: Extinction efficiency
- N(D): Probability to hit a droplet of diameter D

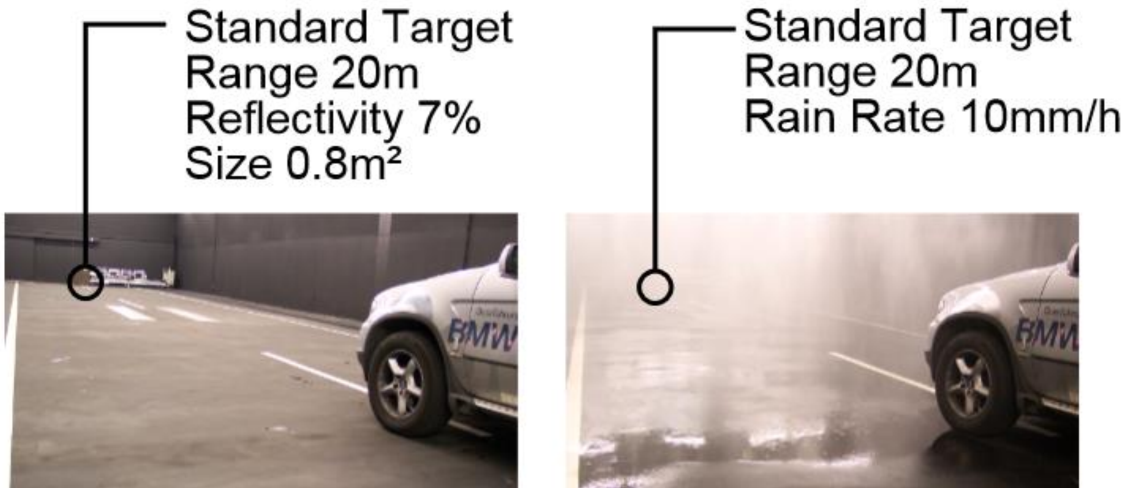
- Backscattering coefficient:

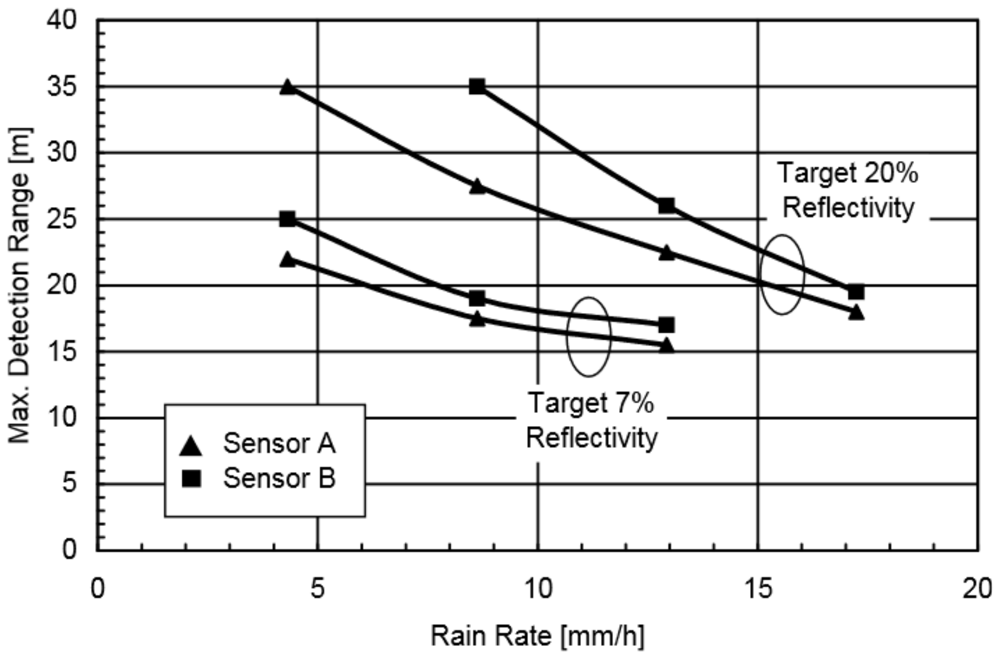
$$\beta = \frac{\pi}{8} \int_{D=0}^{\infty} D^2 Q_{\mathrm{B}}(D) N(D) dD$$

Lidar Simulation – Influence of rain and fog

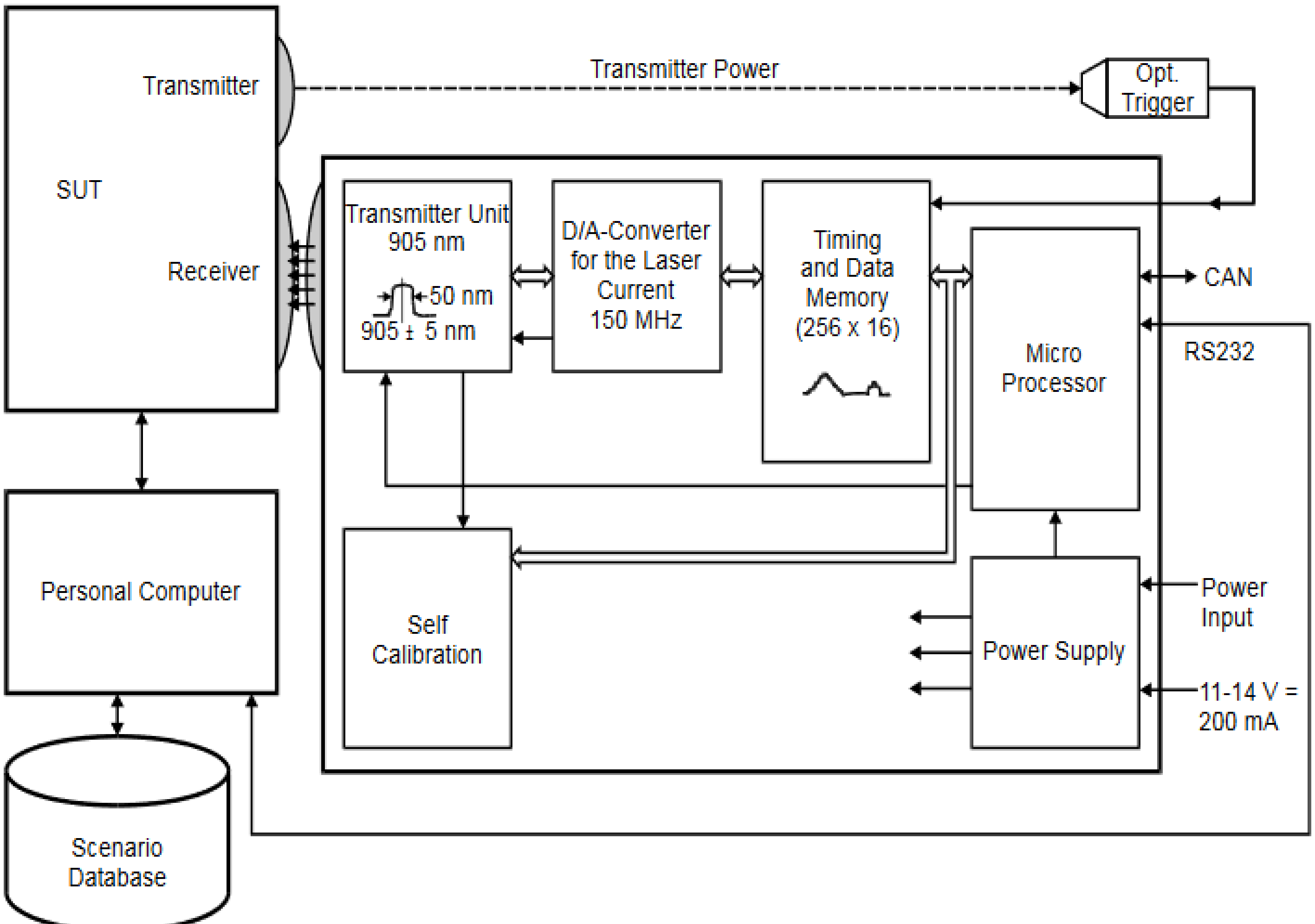


Lidar Simulation – Influence of rain and fog





Lidar Simulation – Influence of rain and fog



Radar utilization in ADAS

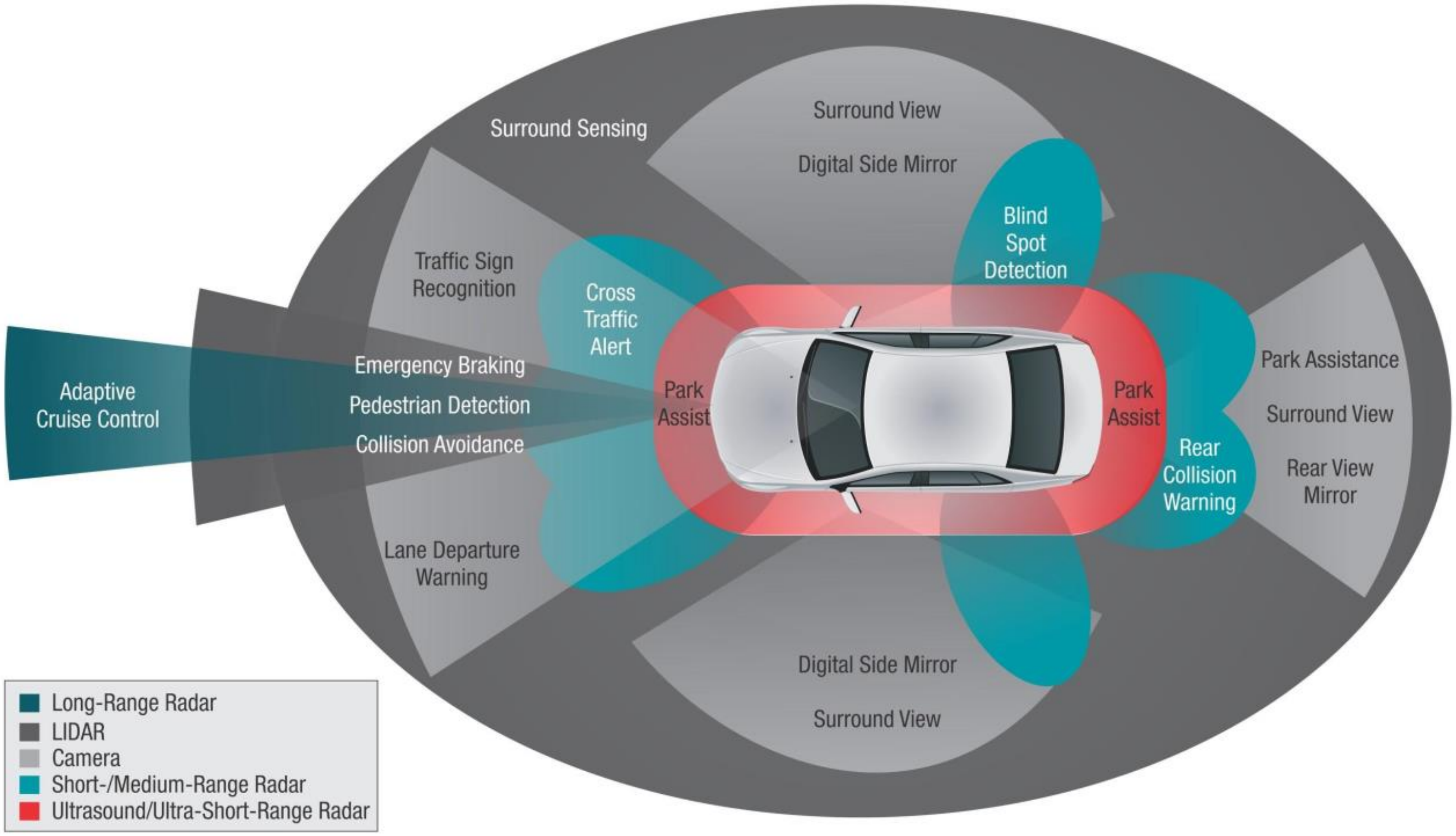


Image: https://e2e.ti.com/blogs /b/behind the wheel/archive/2014/02/04/advancedsafety-and-driver-assistance-systems-paves-the-way-to-autonomousdriving

Radar attenuation across different signal frequency ranges

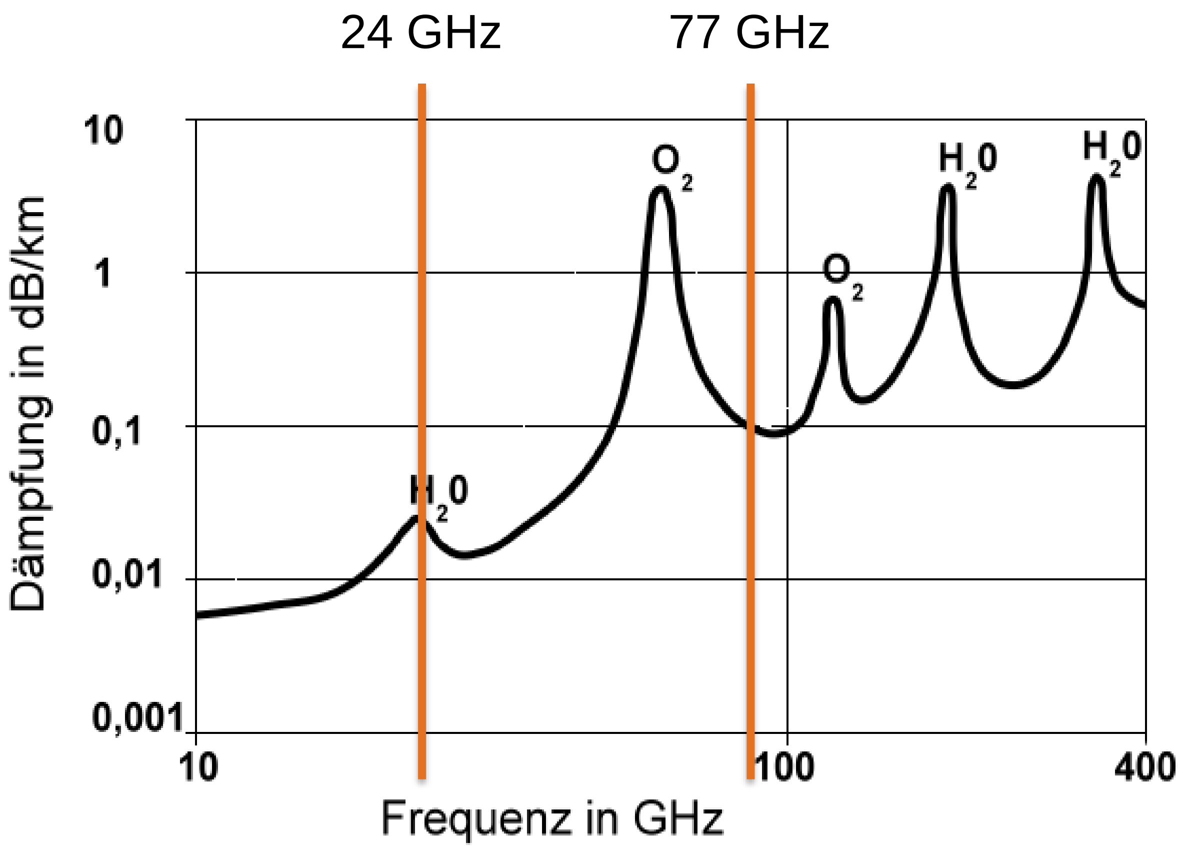
Typical radar frequencies:

24GHz, 77GHz

Note: Sometimes different regulations for stationary (ITS)/non-stationary (AV), regional

Not only frequency matters, but also available modulation bandwidth (Frequency-Modulated Continuous Wave/ FMCW Radar to measure return signal frequency difference).

Higher available modulation bandwidth improves accuracy and resolution.



https://upload.wikimedia.org/wikipedia/commons/7/71/Micrwavattrp.png

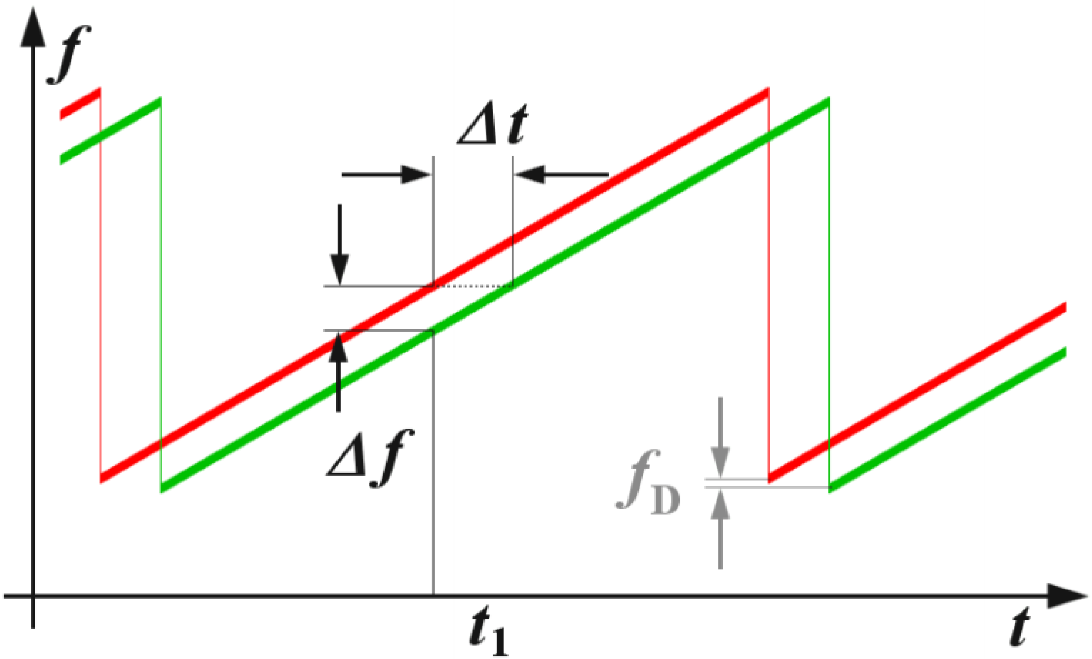
FMCW Radar

Frequency modulated continuous wave radar emits and receives modulated signal frequency patterns.

dt is the time difference between signal transmission and reception.

df is the frequency difference between the received signal and the transmission signal.

Doppler effect and frequency comparison enable direct velocity measurements!



http://www.radartutorial.eu/02.basics/Frequency%20Modulated%20Continuous%20Wave%20Radar.en.html

Radar Architecture Example

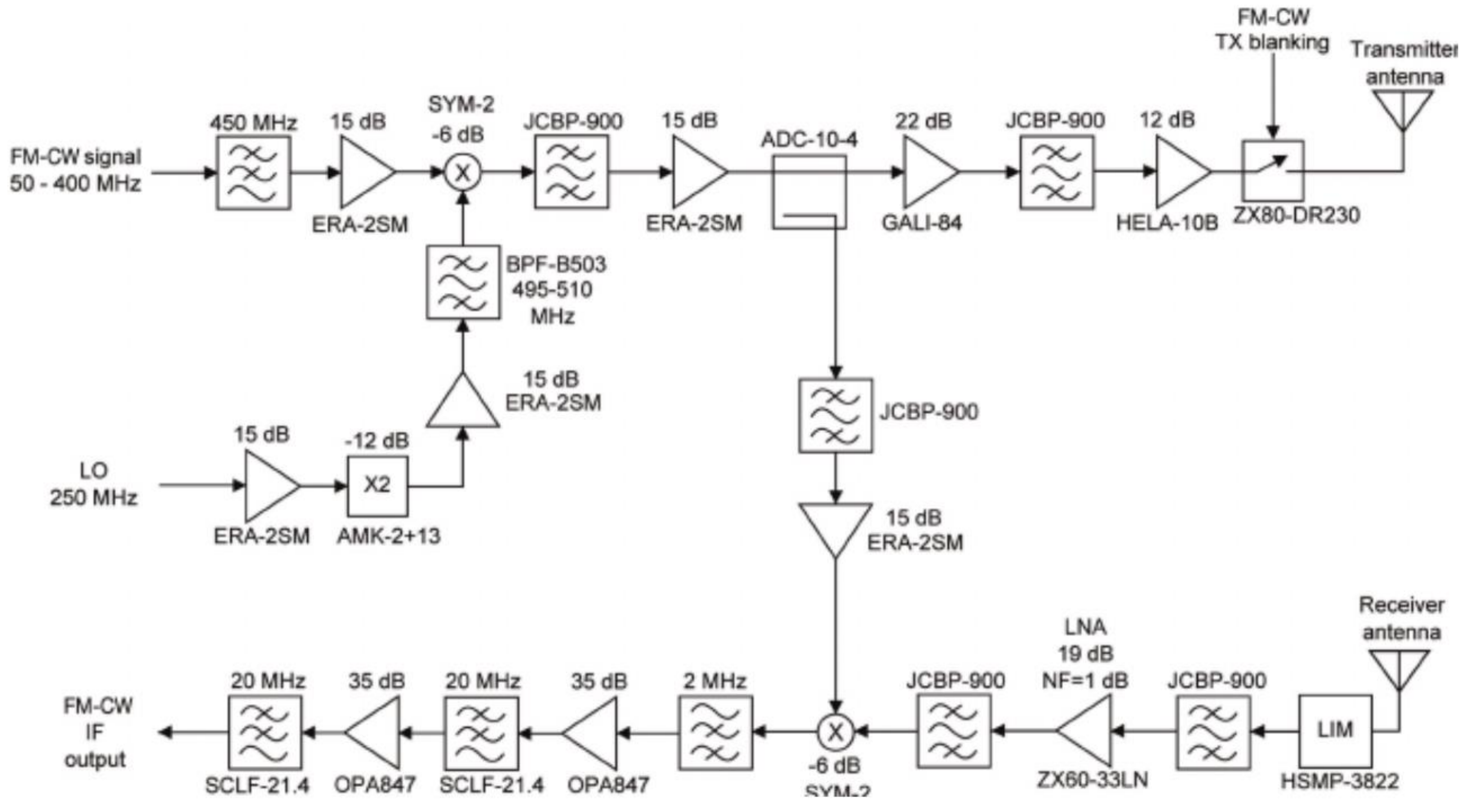


Image:https://upload.wikimedia.org/wikipedia/commons/7/71/Micrwavattrp.png

Frequency modulation (low -> high), demodulation (high -> low), transmission, reception, signal amplification, signal filtering.

Radar Equation

Pt: Transmitted energy

Pr: Received energy

Gt: Transmit antenna gain

Gr: Receive Antenan Gain

σ: Radar cross section (RCS)

λ: Signal wavelength of transmitted signal

R: (Static) Target distance from antenna

$$P_r = P_t \frac{G_t G_r \sigma \lambda^2}{(4 * \pi)^3 * R^4}$$

Radar signal energy drops steeply with the distance. This is caused by the larger space into which the signal will be distributed: the energy of a signal in period Δt is distributed in a specific direction Δϕ in space with volume $4\pi R^2 \Delta t \Delta \phi$, and the reflection on object can be viewed as another emission.

Radar Antenna Gain Patterns

Usually multiple antennas are integrated into an antenna array with tuned phases to focus signal strength, leading to better energy efficiency and reduction of interference from other directions.

Example here: Energy focused in main frontal direction (0°) with a gain of ~15dB.

On the largest side-blob the gain is about -6dB and the gain in the.

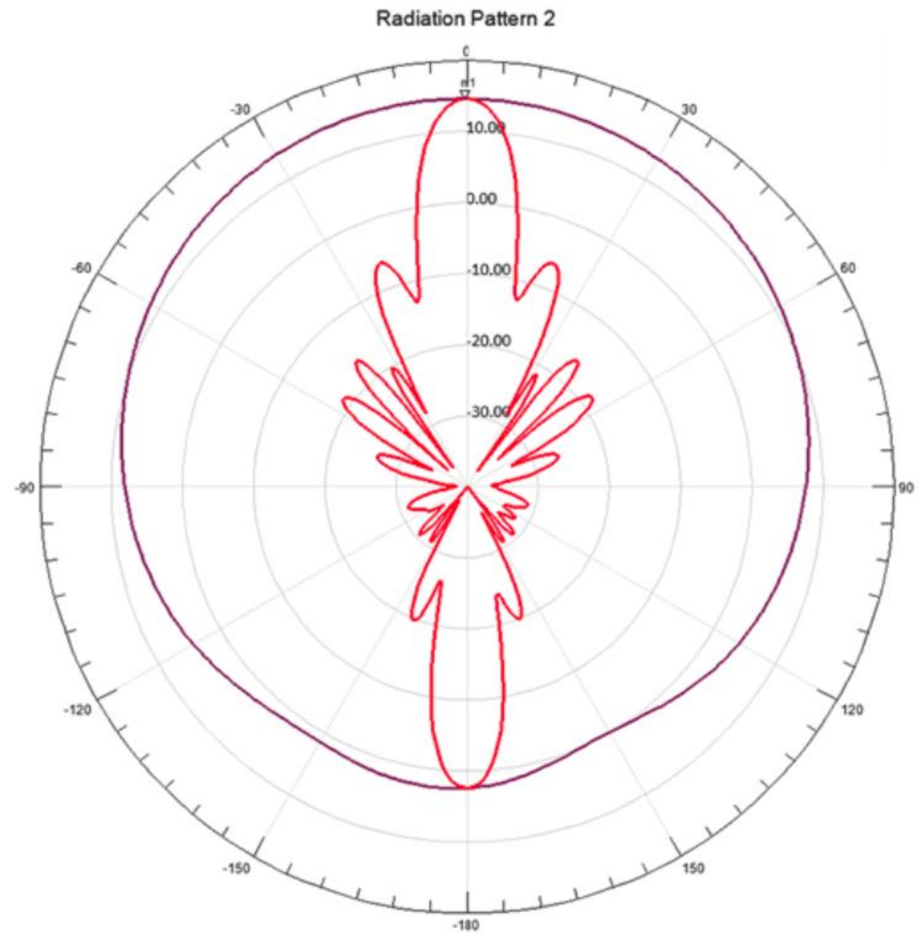
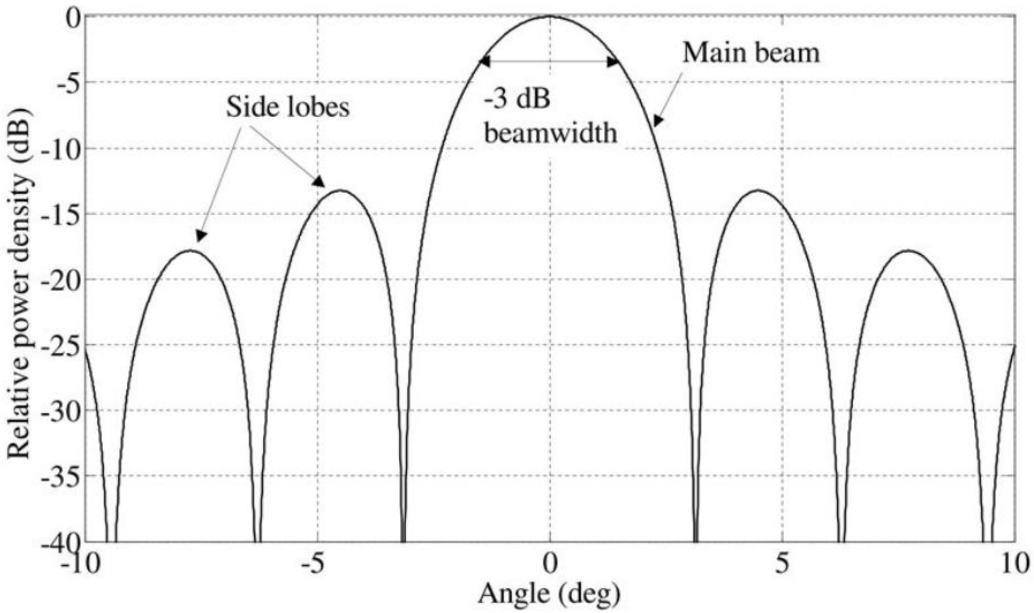


Image: http://www.ansys.com/About-ANSYS/advantage-magazine/Volume-IXIssue-2-2015/radar-road-trip

Radar Antenna Gain Patterns

Alternative visualization of an typical antenna gain pattern.

The resulting pattern can be approximated accordingly.

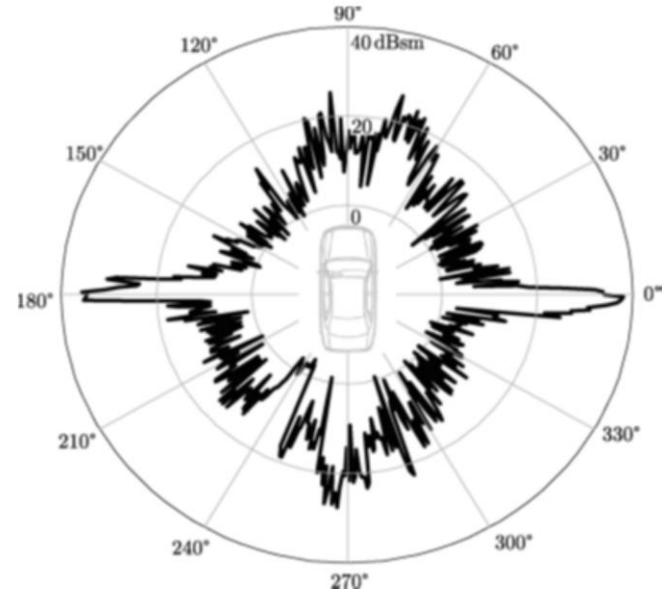


$$P(\theta) = 50 \cdot (\mathrm{abs}(\mathrm{sinc}(100\theta)) - 1)$$

Radar Cross Section (RCS)

An object's ability to reflect a radar signal is for its radar detection.

The property of an object to reflect electromagnetic waves with specific frequency is called the RCS. RCS is defined as the ratio of the reflected energy to the received energy, usually converted to decibel (dB).



Object	RCS (m^2)	RCS (dBsm)
Pickup truck	200	23
Automobile	100	20
Jumbo jet airliner	100	20
Large bomber *or* commercial jet	40	16
Cabin cruiser boat	10	10
Large fighter aircraft	6	7.78
Small fighter aircraft *or* four-passenger jet	2	3
Adult male	1	0
Conventional winged missile	0.5	−3
Bird	0.01	−20
Insect	0.00001	−50
Advanced tactical fighter	0.000001	−60

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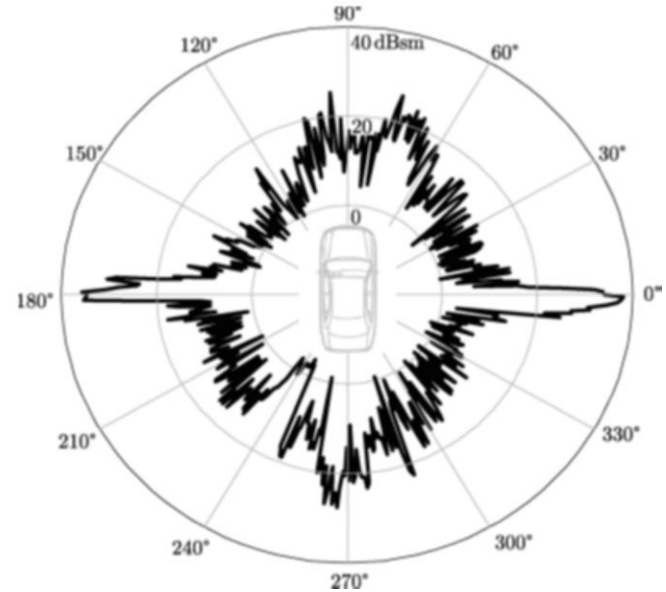
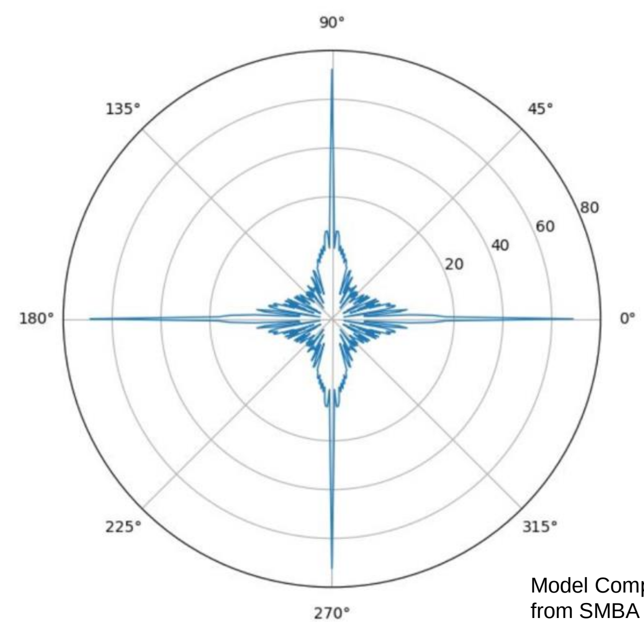
Comparison: RCS of a car vs calculated RCS of a box (useful for simulation).





Model Computation
from SMBA class

Radar Cross Section (RCS)

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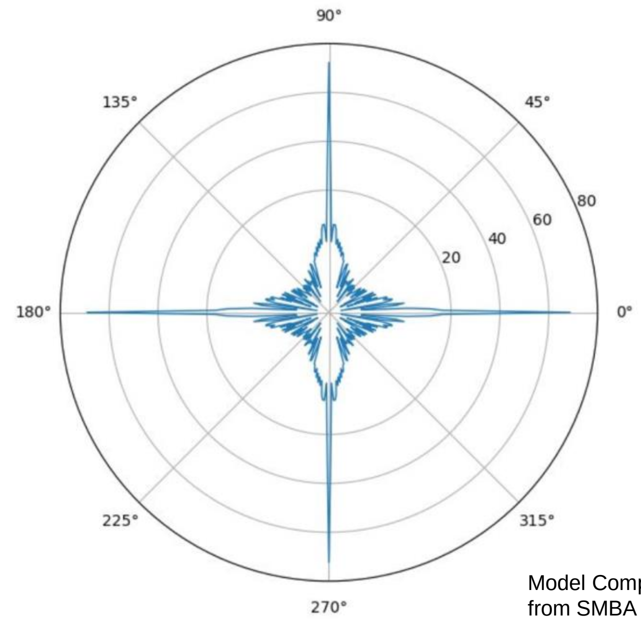
Comparison: RCS of a car vs calculated RCS of a box (useful for simulation).

Maxwell's equations and simplifications are used to derive simulation equations.

w: box width, l: box length

The RCS of a car simplified to be a box, is the sum of the RCS for all surfaces facing the radar.



Model Computation
from SMBA class

$$\hat{n} \times E_o = 0$$
$$\hat{n} \times B_o = 2\hat{n} \times B_i$$
$$\hat{n} \cdot E_o = 0$$
$$\hat{n} \cdot B_o = 0$$

$$E_{PO}(R) = \frac{i\omega}{2\pi}\frac{e^{ikR}}{R}\int (\hat{n} \times B_i) e^{-ik\hat{R}x}$$

$$B_{PO}(R) = \frac{ik}{2\pi}\frac{e^{ikR}}{R}\int (\hat{n} \times B_i) \times \hat{R} e^{-ik\hat{R}x}$$

$$k = \sqrt{\mu\epsilon}\omega$$

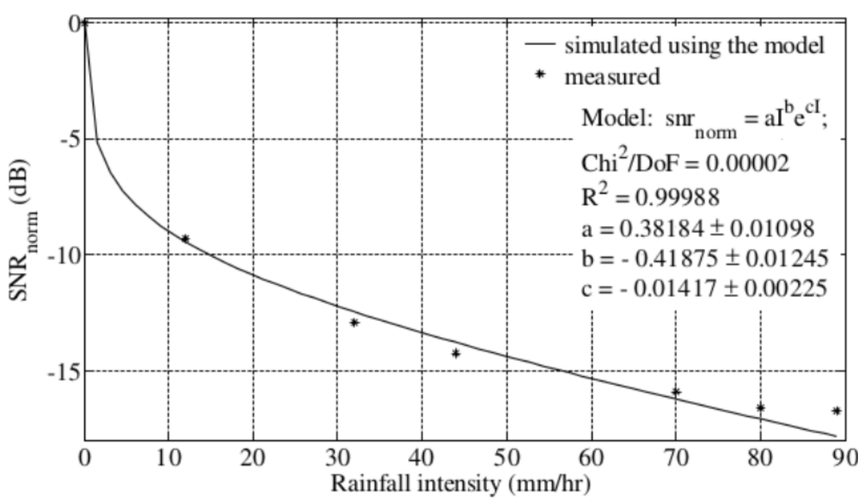
$$\sigma = 4\pi \frac{lw}{\lambda} \cos\theta \frac{\sin lk \sin\theta}{kl \sin\theta}^2$$

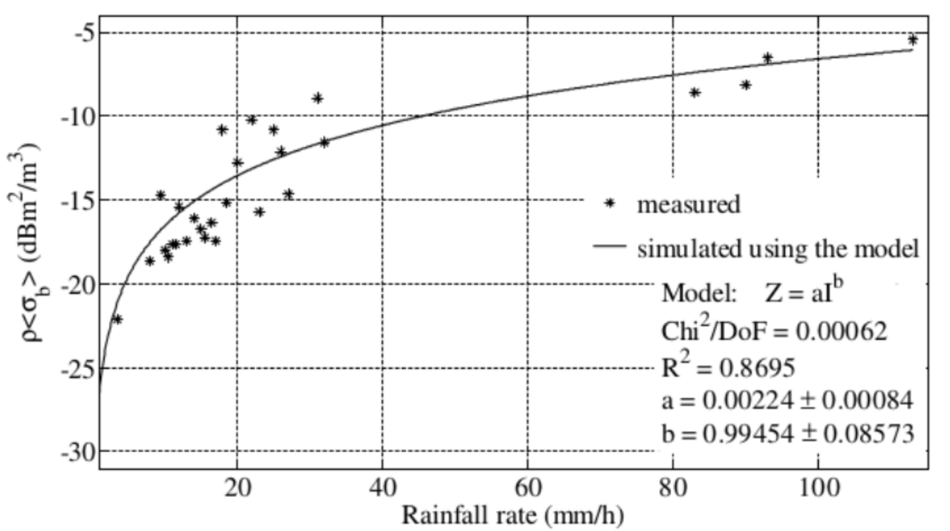
Radar Weather Impact

Weather effects, such as fog, snow, rain or water spray reduce the return signal strength and increase backscattering noise.

Media	*Materials*	*Attenuation*	*backscattering*	*Source*
Air	*fog* $@gm/m^3$	$0.3\ dB/km$		[9]
	snow $@gm/m^3$	$1\ dB/km$	$-50\ dBm^2/m^3$	[10]
	rain $@5mm/hr$	$4\ dB/km$	$-35\ dBm^2/m^3$	[10, 11, 12]
	$@20mm/hr$	$10\ dB/km$	$-23\ dBm^2/m^3$	[11, 13]
	$@50mm/hr$	$20\ dB/km$	$-20\ dBm^2/m^3$	[14, 11]
	spray $@\leq \frac{1}{2}mm$	$0.1\ dB/m$	$-20\ dBm^2/m^3$	[3]
Antenna	*water film*	$30\ dB/mm$	$-3\ dB$	[15]
	ice $@0.5mm$	$2\ dB$	$-5\ dB$	[16]

Indicators for the Signal Degradation and Optimization of Automotive Radar Sensors under Adverse Weather Conditions. Dipl. -Ing. Alebel Arage Hassen. 2006.

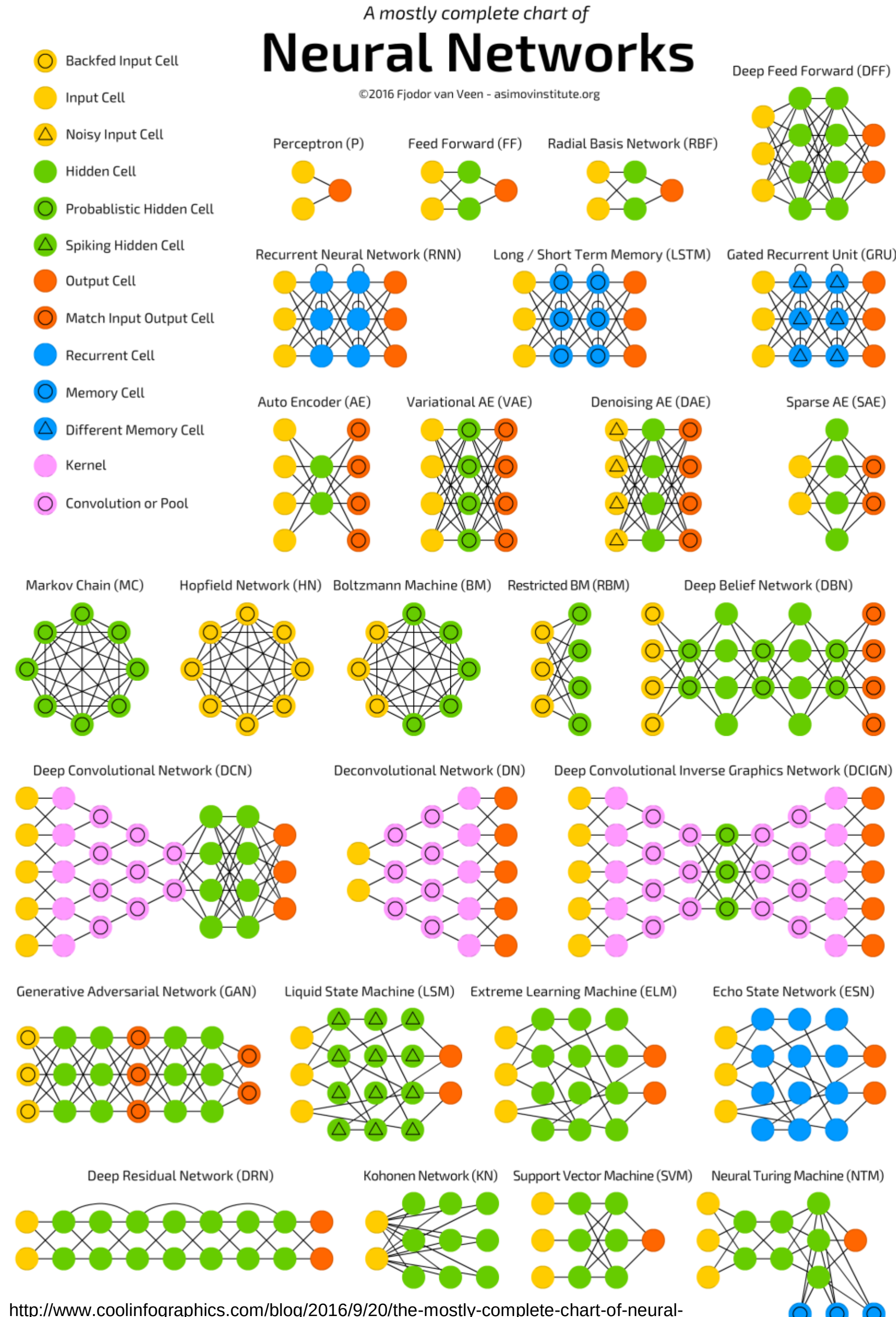




Robotics & Embedded Systems

Deep Learning in Autonomous Driving

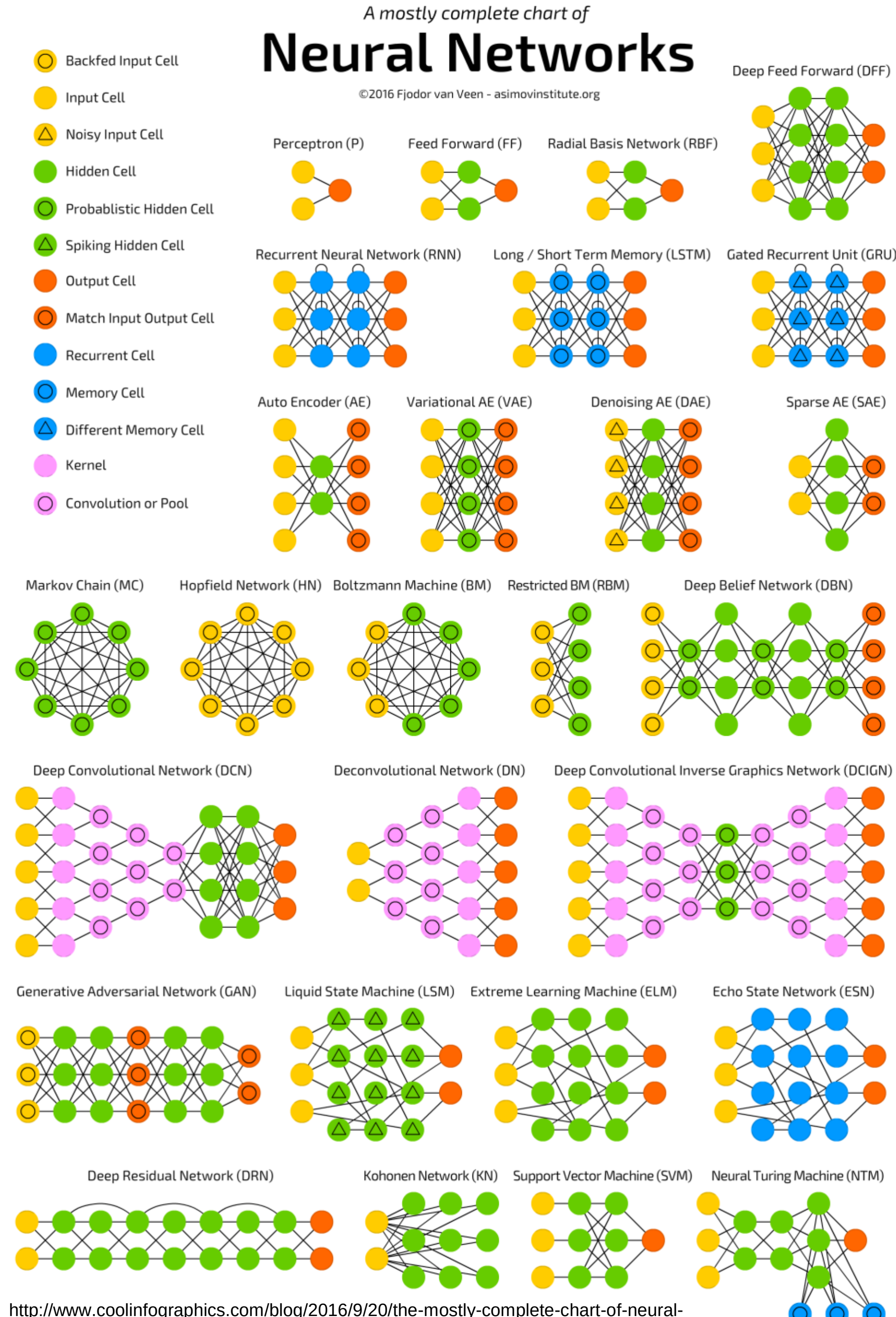
- Neural Networks described in 1943 by Warren McCulloch and Walter Pitts
- Research split in two main directions:
  - Modelling biological processes in the brain
  - Application of neural networks to artificial intelligence
- Expert systems (if-then rules, high-level symbolic) vs low-level (sub-symbolic) Machine Learning



http://www.coolinfographics.com/blog/2016/9/20/the-mostly-complete-chart-of-neural-networks.html

Deep Learning in Autonomous Driving

- AI-Winter
  - "Period of reduced funding and interest in artificial intelligent research. Hype cycles, followed by disappointment and criticisim, followed by funding cuts, followed by renewed interest years or decades later." (wiki)
  - Compare: Dot-Com Bubble, Railway Mania
  - Currently in a hype cycle, supported by strong results



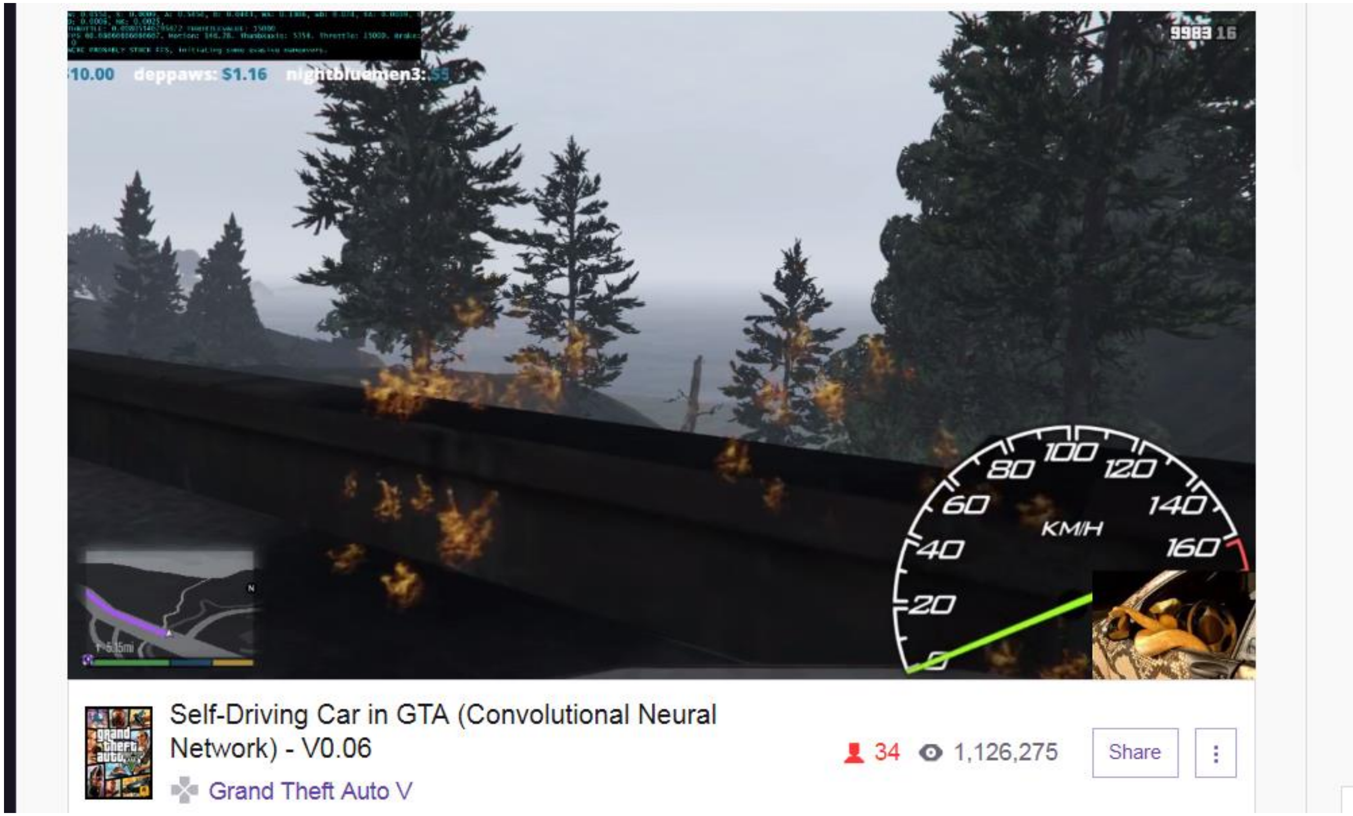
http://www.coolinfographics.com/blog/2016/9/20/the-mostly-complete-chart-of-neural-networks.html

Deep Learning in Autonomous Driving

- Good or Great performance in:
  - Object Detection
  - Image Classification
  - Tracking
  - Games
  - Image generation
  - Speech recognition/generation
  - Traffic prediction
  - Scenario Classification
  - …

Deep Learning in Autonomous Driving

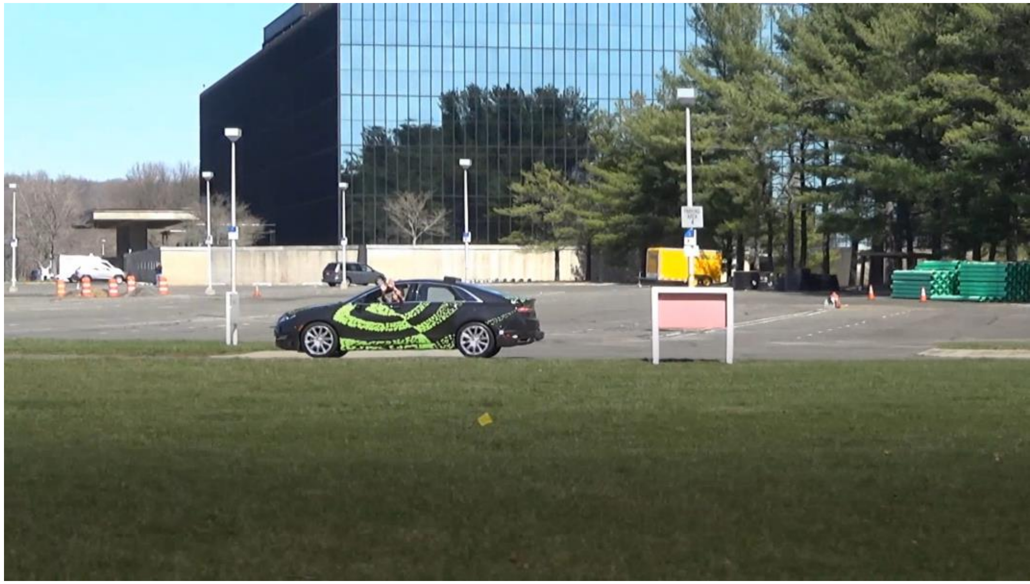
- Good or Great performance in:
  - Games



https://www.twitch.tv/sentdex

Deep Learning in Autonomous Driving

- NVIDIA DAVE2
  - NVIDIA DevBox
  - Torch 7
  - NVIDIA DRIVE PX
  - Network Architecture: CNN
  - Input:
    - Type: Time-stamped video from front-facing camera synced with the steering wheel angle applied by the human driver
    - Road: New Jersey, two-lane roads with and without lane markings, residential streets with parked cars, tunnels and unpaved pathways
    - Weather: Clear, foggy, snowy, rainy, day, night
  - Goal: Map raw pixels from camera to steering commands (end-to-end)

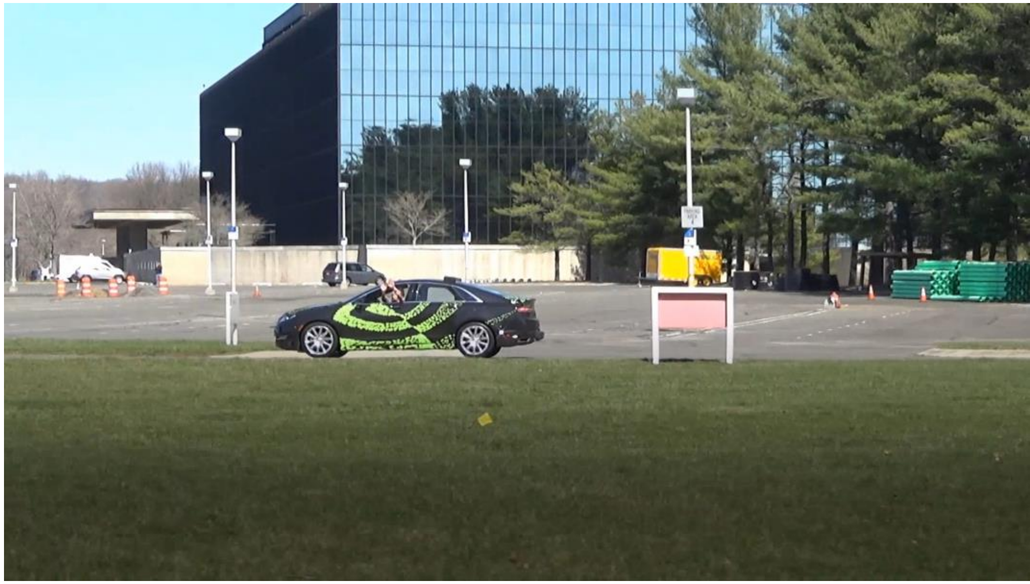


Deep Learning in Autonomous Driving

NVIDIA DevBox

- Four TITAN X GPUs with 12GB of memory per GPU
- 64GB DDR4
- Asus X99-E WS workstation class motherboard with 4-way PCI-E Gen3 x16 support
- Core i7-5930K 6 Core 3.5GHz desktop processor
- Three 3TB SATA 6Gb 3.5” Enterprise Hard Drive in RAID5
- 512GB PCI-E M.2 SSD cache for RAID
- 250GB SATA 6Gb Internal SSD
- 1600W Power Supply Unit from premium suppliers including EVGA
- Ubuntu 14.04
- NVIDIA-qualified driver
- NVIDIA® CUDA® Toolkit
- NVIDIA® DIGITS™ SW
- NVIDIA® cuDNN™
- Caffe, Theano, Torch, BIDMach

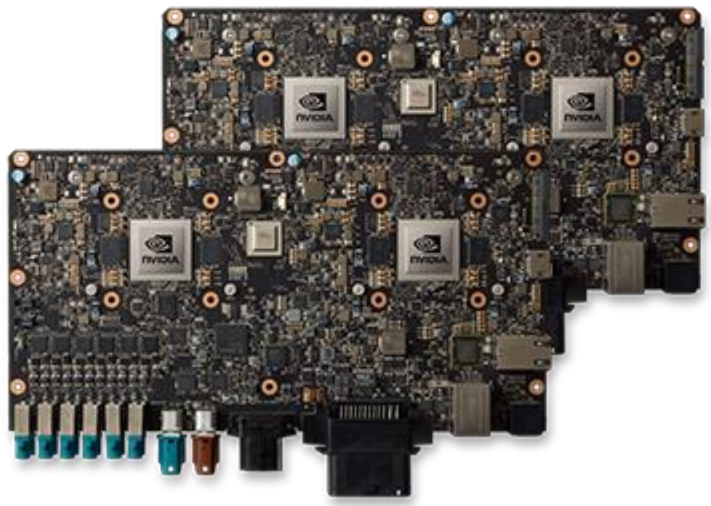
https://developer.nvidia.com/devbox



Deep Learning in Autonomous Driving

NVIDIA Drive PX 2

- 12 Kerne CPU
- Pascal GPU
- 16nm FF Productionprocess
- 8 TFLOPS
- 24 DL_TOPS
- 250W TDP
- Water Cooling

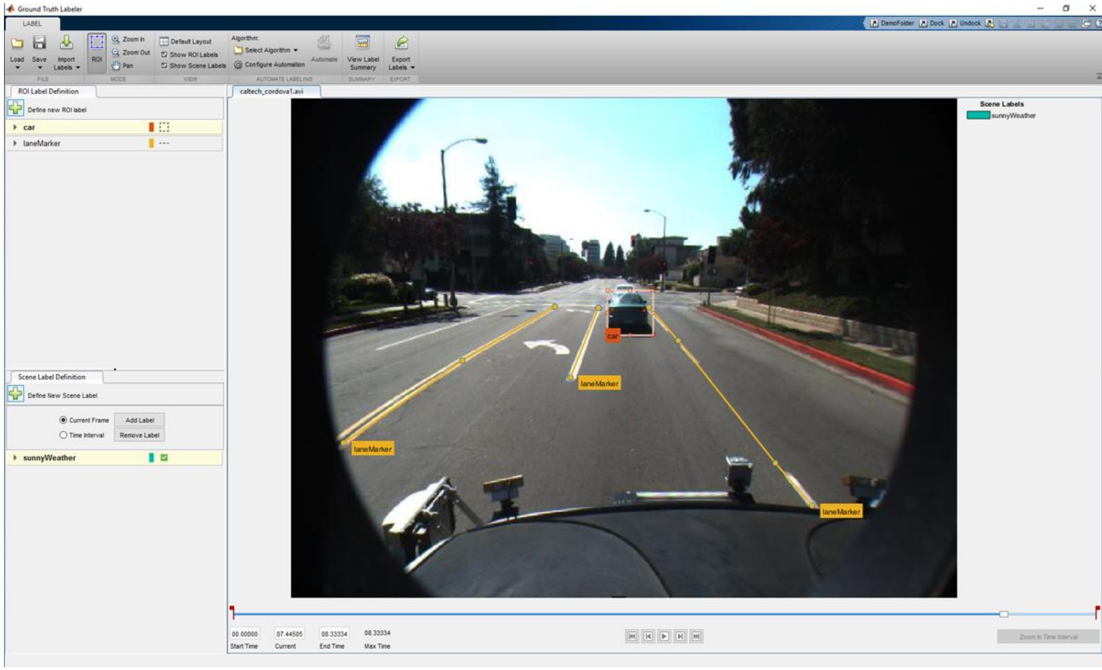


https://www.mobilegeeks.de/artikel/nvidia-drive-px-2/

http://www.nvidia.de/object/drive-px-de.html

Labeling

- Massive Data Sets become available
  - Small data sets with good labels
  - Massive data sets with no labels, not searchable
- (Semi) Automated Labeling is key.
  - Pre-label with pre-trained network/algorithms
  - Fix resulting data batch
  - Retrain labeler with improved labels
  - Repeat
- Often there isn‘t enough data available
  - Color images
  - Rotate Images
  - Cut Images
  - Mirror Images
  - Stretch Images
  - Use pre-trained networks
  - Train on alternative data sets
  - Record moredata
  - …



https://devblogs.nvidia.com/parallelforall/deep-learning-automated-driving-matlab/

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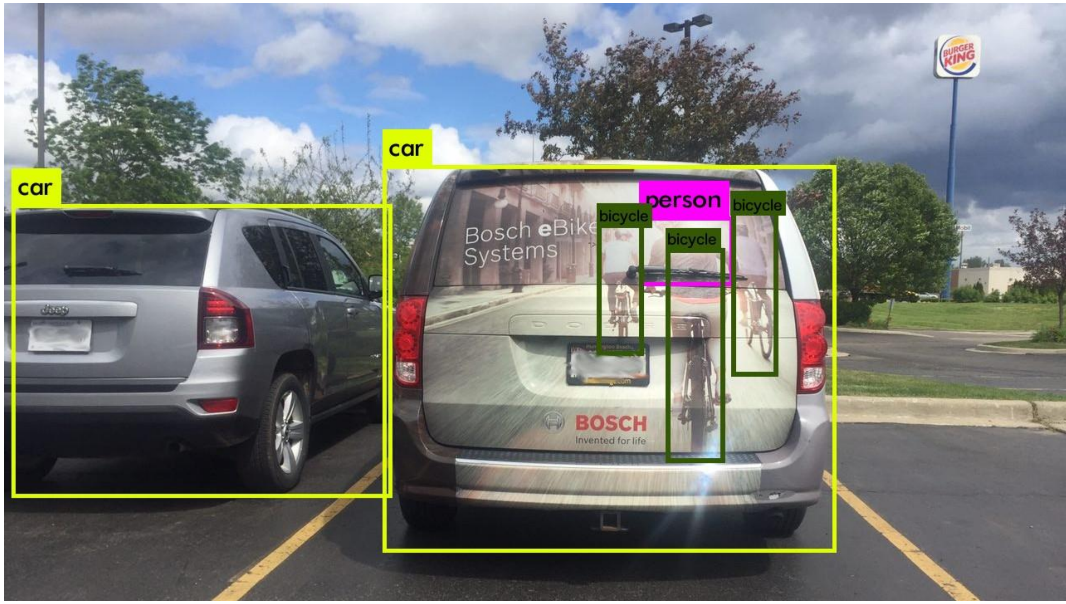
https://devblogs.nvidia.com/parallelforall/deep-learning-automated-driving-matlab/
https://jacquesmattheij.com/sorting-two-metric-tons-of-lego

Not always the best solution, but often promising

Ongoing research questions…

When are neural networks promising?
- Work directly from raw-data without manual feature extraction…
- Complex, hard to describe problems…
- When a lot of data is available…
- When computational cost is less of an issue....
- When high performance has been demonstrated already (image detection etc.)
- …

When to look for other tools?
- Approximate simple functions like f(x)=sin(x)
- Problems that are easy to formally describe in detail
- Very well known engineering problems (dynamic vehicle model on straight road at constant velocity)
- Sometimes simpler solutions from control theory
- Sometimes lower computational cost via classical algorithms
- When formal verification is required (Safety, Greybox)
- …?

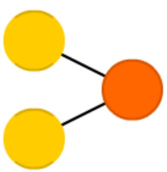


https://www.technologyreview.com/s/608321/this-image-is-why-self-driving-cars-come-loaded-with-many-types-of-sensors/

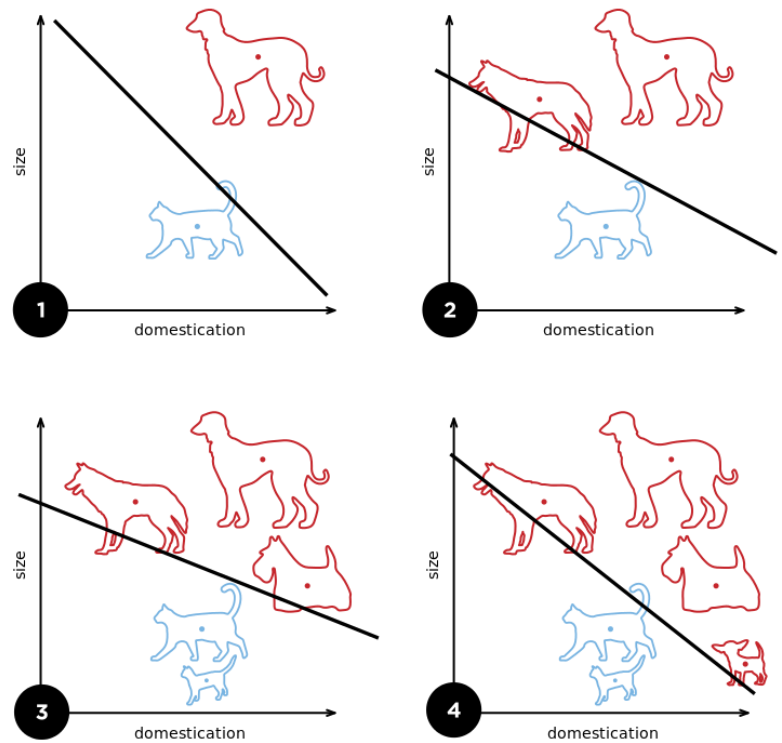
Deep Learning in Autonomous Driving

- Perceptron: A binary classifier; linear classifier; 1950s
- Is this a road or not?...

Perceptron (P)



$$f(x) = \begin{cases} 1 & \text{if } w \cdot x + b > 0 \\ 0 & \text{otherwise} \end{cases}$$

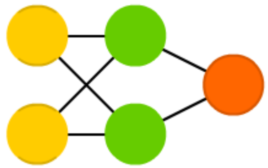


https://en.wikipedia.org/wiki/Perceptron

Deep Learning in Autonomous Driving

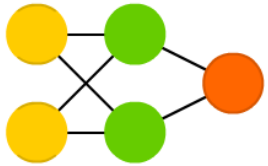
- Network with units where connections do not form a cycle (no Feedback connections):
  - Feedforward neural network

Feed Forward (FF)



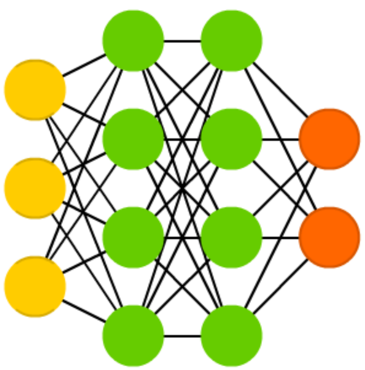
- Different activation functions can be better for specific data
  - With radial basis functions: Radial Basis Network (RBF)

Radial Basis Network (RBF)



Deep Learning in Autonomous Driving

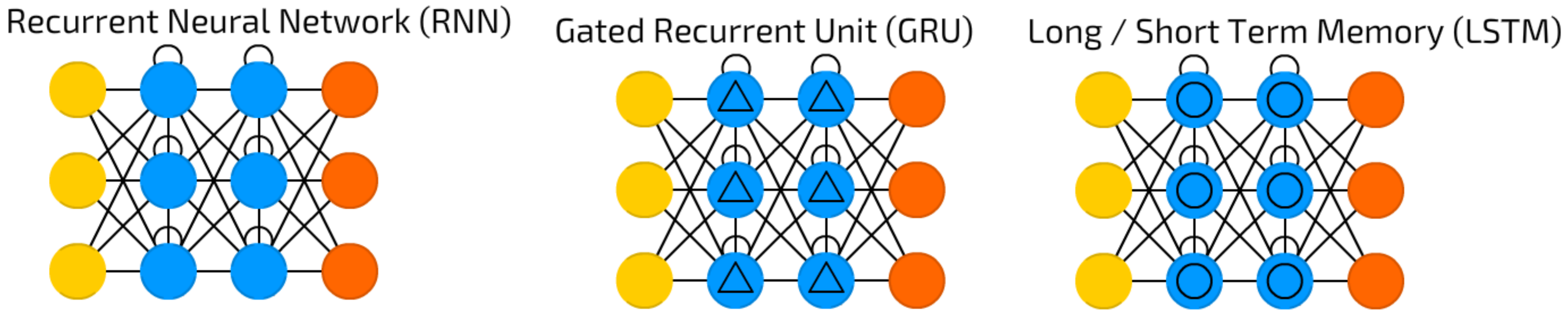
- With additional layers: Deep Feedforward Network / Multiplayer Perceptron (MLP)



- Added depth often leads to improved performance, but higher computational cost, also impacts training difficulty. Need a lot of data. Layers often take over hierarchical tasks (Image detection; from low-level to high-level features). For complex problems (not approximations of a simple function).

Deep Learning in Autonomous Driving

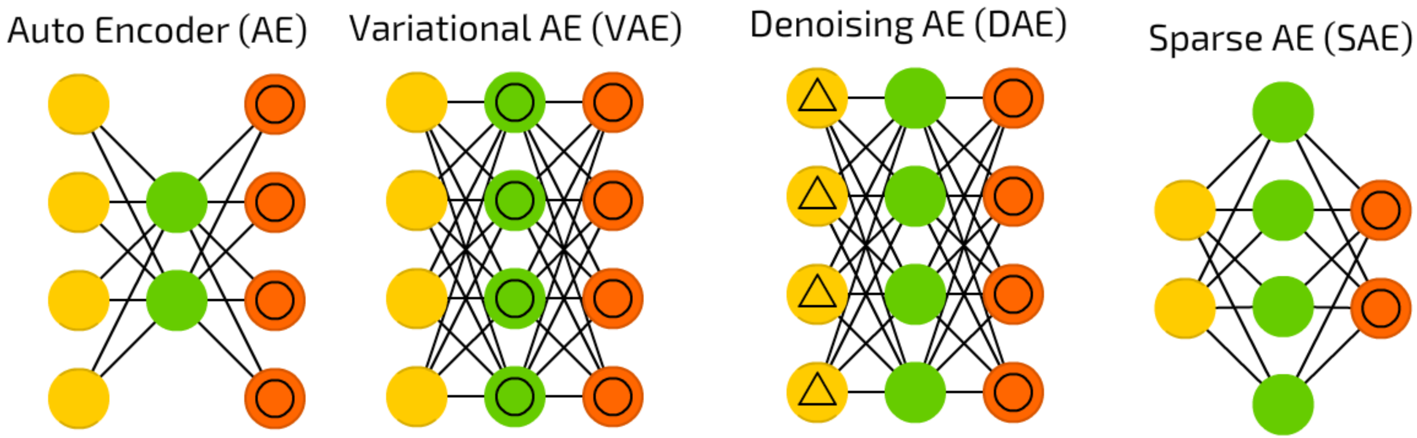
- Recurrent Neural Network: Connections between units form a directed cycle to exhibit dynamical temporal behavior. (Use last state to calculate next state)
- Gated Recurrent Unit (GRU): Similar to RNN, but only conditionally use last state for calculation of next state
- Long/Short-Term Memory (LSTM): More gates. Better insensitivity to gap length.



- Successful for speech recognition, handwriting recognition, processing of arbitrary sequences of inputs.

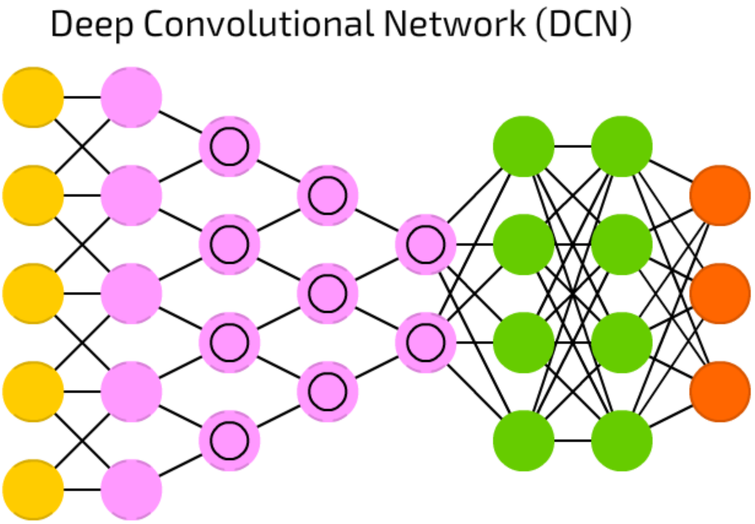
Deep Learning in Autonomous Driving

- Autoencoder: Useful for Pre-Training; Reduce data to information rich nodes and reconstruct inputs. Yields good weights for feature extractor part.



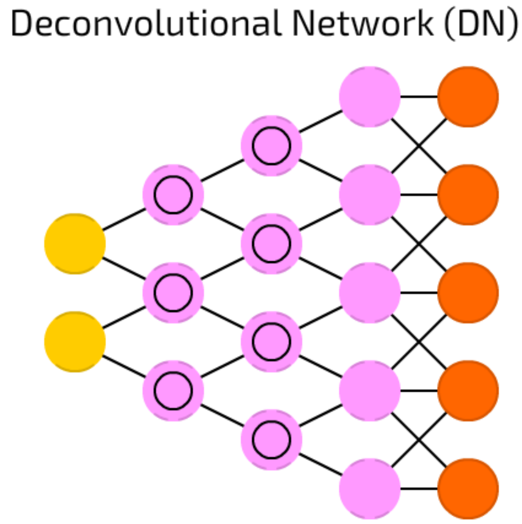
Deep Learning in Autonomous Driving

- Deep Convolutional Network (DCN): Multiple convolutional layer.



Deep Learning in Autonomous Driving

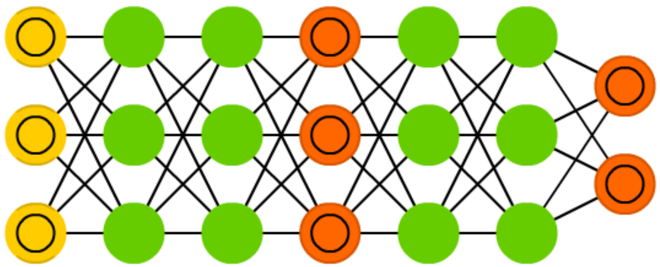
- Deconvolutional Network (DN): Opposite of convolutional network. (Generate Output from reduced input)



Deep Learning in Autonomous Driving

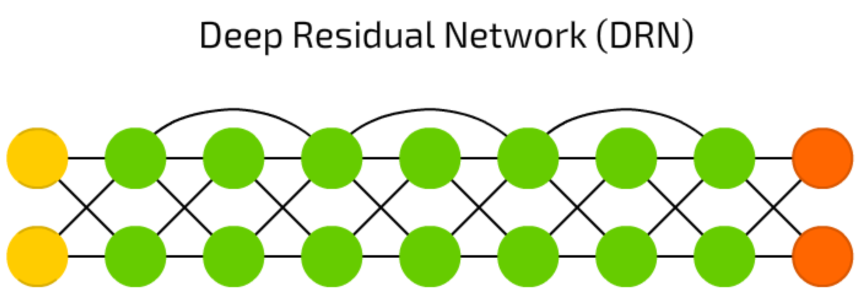
- Generative Adversarial Network (GAN): Noise based fake-image generator and original image – Network compares both and identifies true image.

Generative Adversarial Network (GAN)



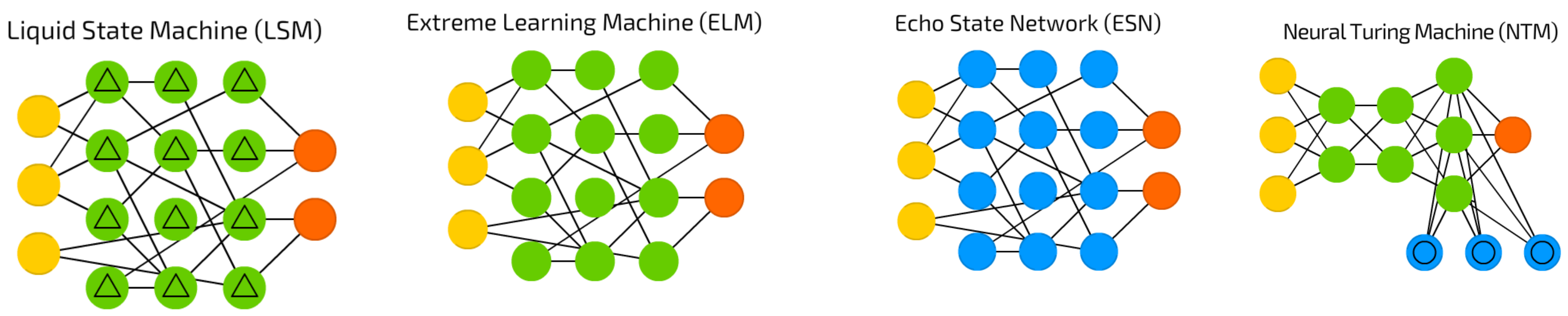
Deep Learning in Autonomous Driving

- Deep Residual Network (DRN): Deep networks sometimes result in small gradients (vanishing or exploding gradient problem). Residual networks facilitate training of deep neural networks.



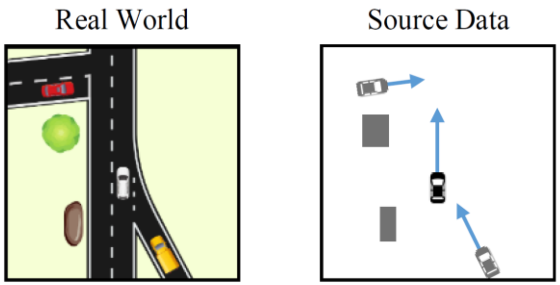
Deep Learning in Autonomous Driving

- Liquid State Machine (LSM): A Type of spiking neural network (more biologically plausible, but limited applicability at the moment). Liquid State Machine means nodes are randomly connected to each other.
- Many other types of networks available and under research…

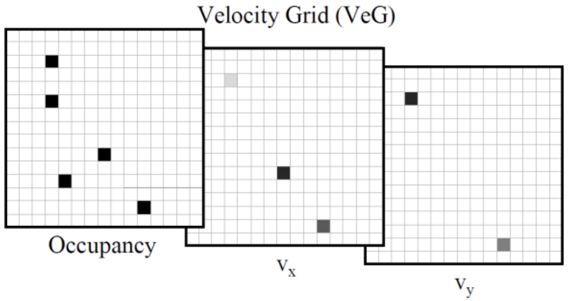


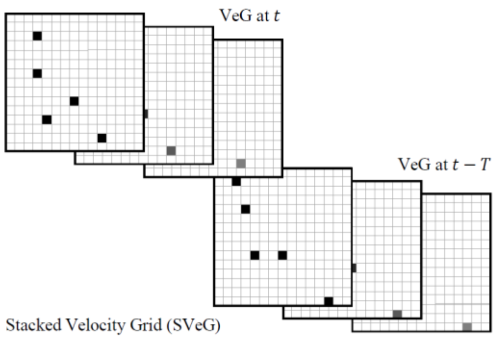
Deep Learning in Autonomous Driving

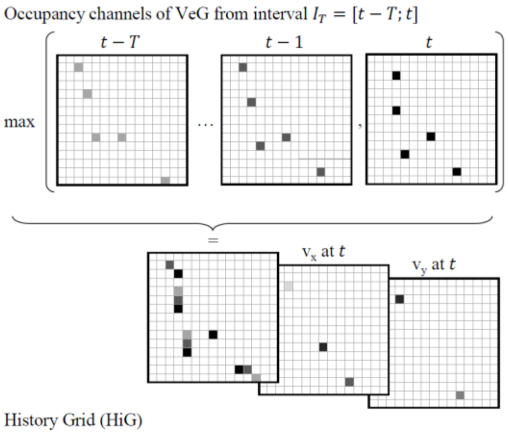
- Example Scenario Classification and Prediction
  (“Spatiotemporal representation of driving scenarios and classification using neural networks, Gruner, Hezler, Hinz et. Al., IV 2017)
  - Use fused sensor data as input:



  - Choose Data Representation Format:

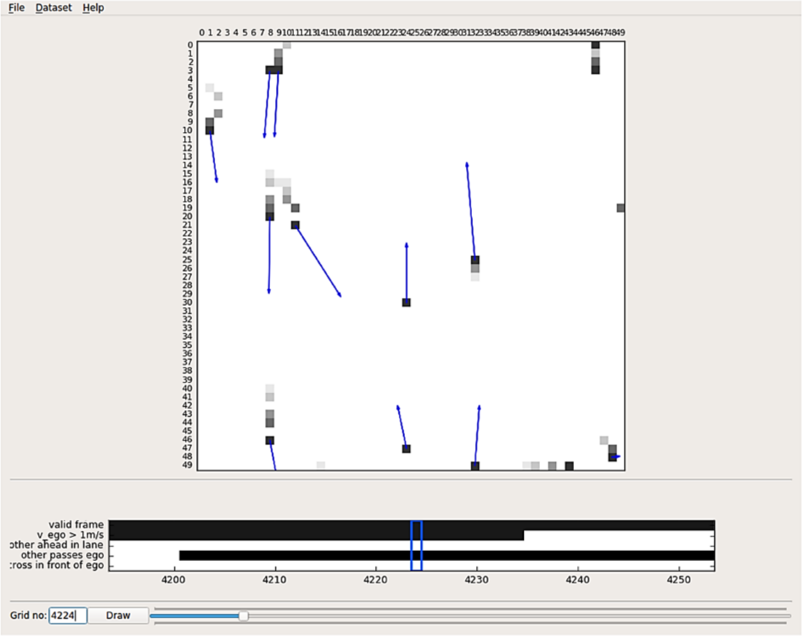


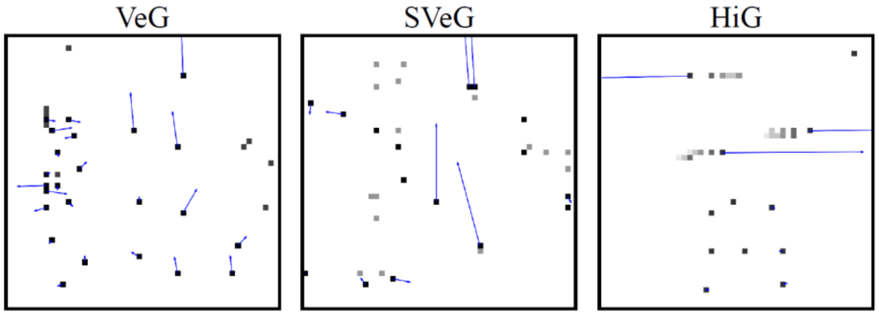




Deep Learning in Autonomous Driving

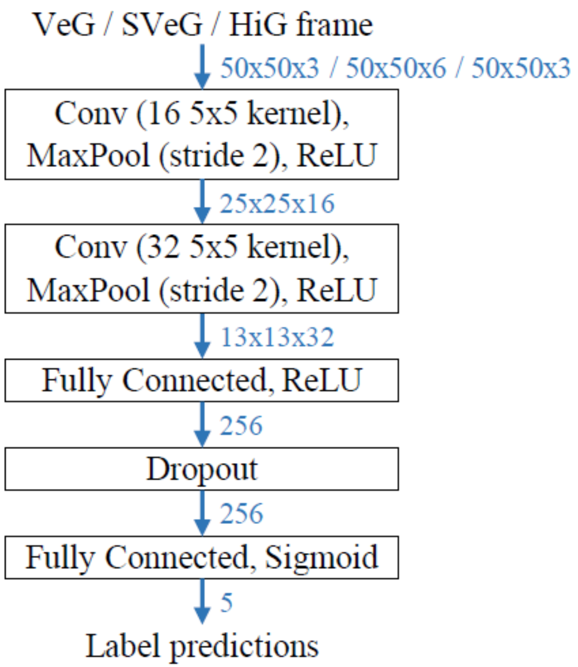
- Example Scenario Classification and Prediction
  - Use fused sensor data as input
  - Choose Data Representation Format
  - Label Data:





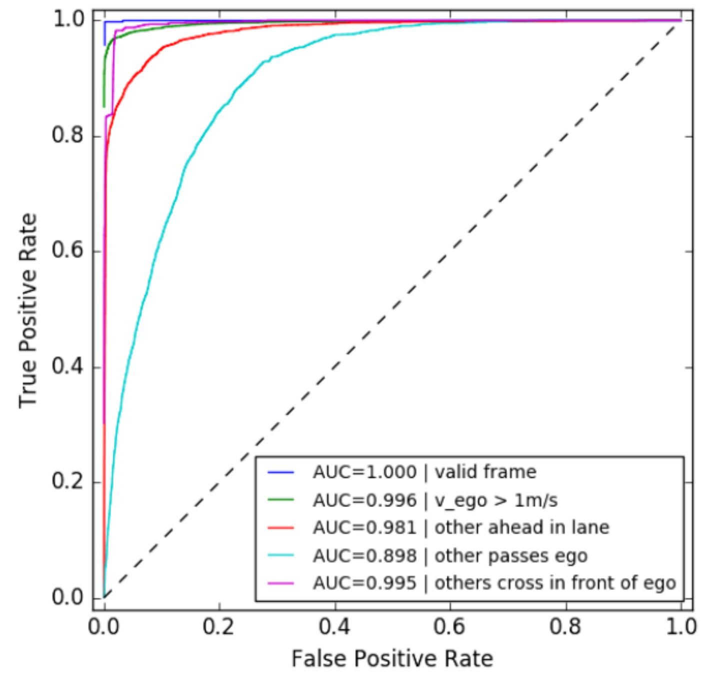
Deep Learning in Autonomous Driving

- Example Scenario Classification and Prediction
  - Use fused sensor data as input
  - Choose Data Representation Format
  - Label Data
  - Generate additional data (stretch…)
  - Choose Network Architecture



Deep Learning in Autonomous Driving

- Example Scenario Classification and Prediction
  - Use fused sensor data as input
  - Choose Data Representation Format
  - Label Data
  - Generate additional data (stretch…)
  - Choose Network Architecture
  - Evaluate Network Performance



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