EUROPEAN RESEARCH PROJECT AI-SEE: ARTIFICIAL INTELLIGENCE TO IMPROVE VEHICLE VISION FOR AUTOMATED DRIVING IN POOR VISIBILITY CONDITIONS – OVERVIEW AND LATEST RESULTS.

Summer School Porto Heli

Dr. Werner Ritter
Mercedes-Benz AG

- Motivation
- Architecture of the AI-SEE platform
- Components of the platform

06.09.2023

https://www.ai-see.eu/ Project duration 01.06.2021 to 31.12.2024

HOW CAN WE ENSURE THAT
AUTOMATED VEHICLES DRIVE RELIABLY
EVEN IN ADVERSE WEATHER CONDITIONS?

THE GOAL

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- Develop a **robust and fault-**tolerant novel sensing technology and associated AI
- Enable automated driving in **all relevant weather & lighting conditions** (snow, heavy rain, fog)
- Permit safe driving **24h/365-days**

THE CHALLENGE

Source: ibeo

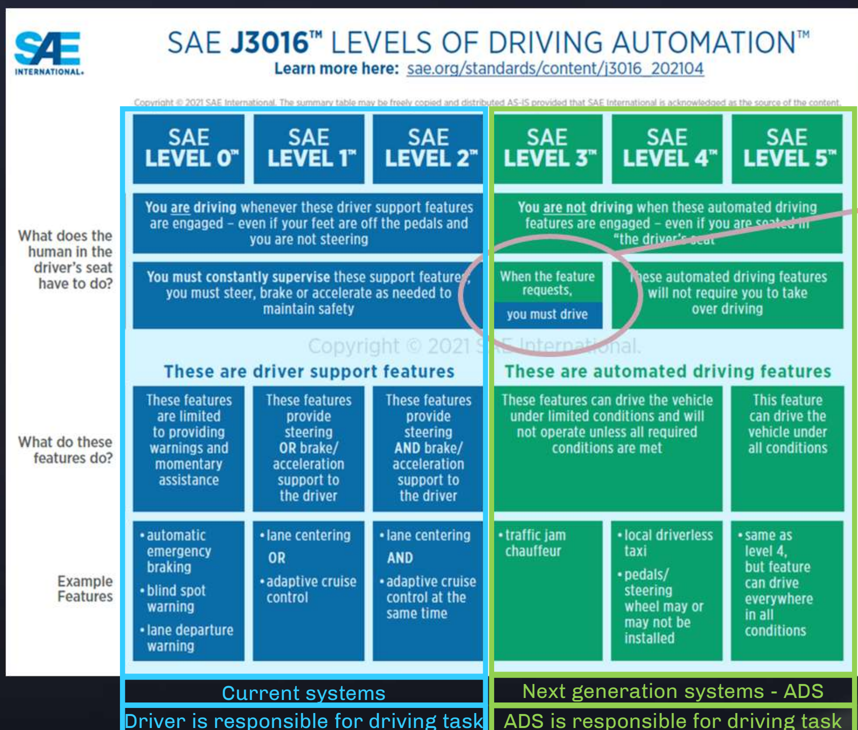
THE CHALLENGE

- Currently commercialization of automated vehicles is dificult due to their **inability to drive under any relevant weather and lighting conditions.**
- Testing takes place in **small designated areas with good weather conditions.**
- Prototypes **struggle or completely fail** in adverse weather.

Source: ibeo

THE CHALLENGE

Mandatory: For safety reason as a minimum, the L3 system must be able to detect and delegate the driving task back to the driver on time if inoperability is foreseeable:



Next Generation L3 systems
The AD System is liable!

The system must independently detect its inoperability in e.g. adverse weather! and inform the driver to take over

The system should (somehow) work even in adverse weather for safety and availability reasons

IT NEVER RAINS IN CALIFORNIA …. BUT CERTAINLY AROUND IT IN THE WORLD

CALIFORNIA ISSUES PERMITS TO CRUISE, WAYMO FOR AUTONOMOUS VEHICLE SERVICE, BUT ….

WASHINGTON, FEB 28 (REUTERS) 2022 - THE CALIFORNIA PUBLIC UTILITIES COMMISSION (CPUC) ON MONDAY ISSUED PERMITS TO SELF-DRIVING UNITS OF GENERAL MOTORS (GM.N) AND ALPHABET INC (GOOGL.O) TO ALLOW FOR PASSENGER SERVICE IN AUTONOMOUS VEHICLES WITH SAFETY DRIVERS PRESENT.

STARTING MONDAY, CRUISE IS ALLOWED TO PROVIDE THE "DRIVERED DEPLOYMENT" SERVICE ON SOME PUBLIC ROADS IN SAN FRANCISCO BETWEEN THE HOURS OF 10 P.M. AND 6 A.M. AT SPEEDS OF UP TO 30 MILES PER HOUR, WHILE WAYMO CAN OFFER SERVICE IN PARTS OF SAN FRANCISCO AND SAN MATEO COUNTIES AT SPEEDS OF UP TO 65 MILES PER HOUR, CPUC SAID. **NEITHER COMPANY IS ALLOWED TO OPERATE DURING HEAVY FOG OR HEAVY RAIN**.

FOG BROUGHT 5 ADS WAYMO VEHICLES TO A HALT IN THE MIDDLE OF THE ROAD

San Francisco Chronicle, April 11, 2023

BAY AREA

Waymo says dense S.F. fog brought 5 vehicles to a halt on Balboa Terrace street

Rachel Swan
April 11, 2023 | Updated: April 11, 2023 2:55 p.m.

Foggy conditions prompted the software of multiple autonomous vehicles to stop on San Aleso Avenue in San Francisco early Tuesday morning, blocking traffic for several minutes.
Gene Valla

Five self-driving vehicles blocked traffic early Tuesday morning in the middle of a residential street in San Francisco's Balboa Terrace neighborhood, apparently waylaid by fog that draped the southwestern corner of the city.

The **software-powered convoy had run into "very dense fog and determined they should pull over temporarily,"** Waymo spokesperson Chris Bonelli said, explaining how **five of the company's cars wound up clogging a right lane** of San Aleso Avenue down to the crosswalk, with **one car straddling the center lane**. They moved on after the fog cleared, which, according to bystanders, took several minutes.

Waymo is planning software updates to "improve our fog and parking performance to address such situations in the future," Bonelli said.

Baffled motorists flashed headlights and tried to maneuver around the jam, which occurred shortly before 6 a.m. — the latest traffic disruption by seemingly ubiquitous robotaxis that treat San Francisco streets as a testing ground. One resident who began snapping cell phone photos saw the cars were outfitted with cameras and sensors, and that a rear passenger door bore the all-caps logo for Waymo, a Mountain View company that began as Google's self-driving car project.

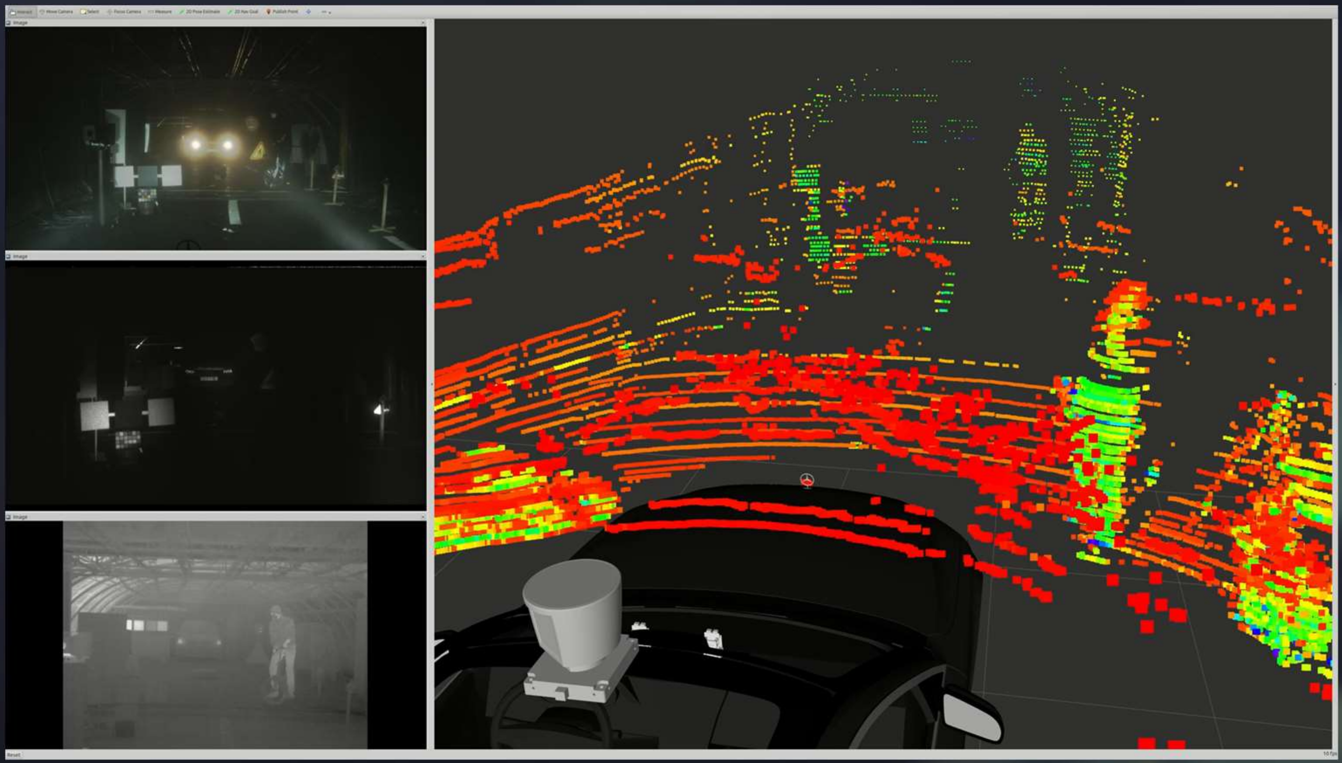
"They were just idling," Balboa Terrace resident Gene Valla said, describing how he encountered the high-tech fleet while trying to make a right-hand turn from Monterey Boulevard onto San Aleso Avenue. Impeded by the vehicle in the intersection, Valla blinked his headlights, then got out of his car to investigate. When he peered into the window, he saw no one in the driver's seat.

By that point, another driver was heading the other way down San Aleso, shining headlight beams as he gingerly squeezed past the cluster of autonomous cars. Valla gave up, backed out of the intersection and drove around the block to park in front of his house. He estimated the self-driving cars were halted for at least six minutes before he saw the first one glide away.

A spokesperson for the San Francisco Municipal Transportation Agency said the city is compiling reports of road disturbances by autonomous vehicles, though officials have no "systemic data." Although the SFMTA frequently fields complaints about autonomous vehicles, the California Public Utilities Commission regulates them.

CURRENTLY INSTALLED SENSORS DEGRADE STRONGLY IN ADVERSE WEATHER CONDITIONS !

STRONG PERFOMANCE DEGRADATION IN BAD WEATHER, e.g. Fog with 50m-60m visibility range



- **Stereo camera**
  only short visibility and invisible pedestrians next to a blinding car headlight
- **Our development: Gated camera**
  larger visibility and less problems with backscattering/airlight
- **Lidar**
  lots of reflections directly in front

- **Pedestrians at a distance of approx. 30 m from the vehicle can not be detected (not visible) with either the LiDAR or the conventional camera.**

- **These are only "visible" here with a thermal imaging or a gated camera.**

COULD WE ALLOW TO DRIVE A CAR BLIND?

Just for 10 seconds (= min. return time for SAE L3)??

Just for 278 m at a speed of 100km/h (60 mph)

Just for the length of 3 soccer fields

Definitely NOT !!!!

Not even once !!!!

… or 1083 m in 30 sec at a speed of 130km/h (80 mph)

ADVERSE WEATHER HAPPENS IN EU A WAY OFTEN THAN WE THINK

Annual averages for rainfall plus snowfall (EU major cities)

Days	City	Inches	Millimetres
132	Amsterdam, Netherlands	33.0	838
119	Andorra la Vella, Andorra	37.5	952
43	Athens, Greece	14.4	365
55	Barcelona, Spain	25.2	640
95	Belgrade, Serbia	27.2	691
106	Berlin, Germany	22.5	571
125	Birmingham, United Kingdom	26.8	681
170	Glasgow, United Kingdom	44.3	1124
129	Hamburg, Germany	30.4	773
115	Helsinki, Finland	26.9	682
84	İstanbul, Turkey	31.7	805
101	Kazan, Russia	21.6	548
81	Kharkiv, Ukraine	20.7	525
99	Kiev, Ukraine	25.6	649

Days	City	Inches	Millimetres
152	Leeds, United Kingdom	40.3	1024
127	Lille, France	29.2	743
77	Lisbon, Portugal	28.6	726
115	Ljubljana, Slovenia	53.9	1368
109	London, United Kingdom	21.9	557
122	Luxembourg, Luxembourg	34.5	876
104	Lyon, France	32.8	832
63	Madrid, Spain	17.2	436
112	Nizhny & Novgorod, Russia	22.0	558
68	Odessa, Ukraine	18.3	464
113	Oslo, Norway	30.0	763
111	Paris, France	25.1	637
101	Podgorica, Montenegro	65.4	1661
94	Prague, Czech Republic	20.7	526
120	Pristina, Kosovo	23.5	598

Days	City	Inches	Millimetres
148	Reykjavik, Iceland	31.4	798
120	Riga, Latvia	25.0	636
78	Rome, Italy	31.4	799
86	Rostov-on-Don, Russia	23.4	595
131	Rotterdam, Netherlands	33.7	856
119	Saint Petersburg, Russia	24.9	633
95	Samara, Russia	22.1	561
76	San Marino, San Marino	25.8	655
84	Valletta, Malta	21.8	553
98	Vienna, Austria	25.6	651
122	Vilnius, Lithuania	26.9	683
73	Volgograd, Russia	15.9	403
93	Warsaw, Poland	20.3	515
95	Zagreb, Croatia	33.1	840
125	Zurich, Switzerland	41.2	1048

Rain and snowfall in EU >100 days per year

(calculation includes only days with precipitation at least one mm (0.04 inches).

!L3 System predictive detection & availability in bad weather is imperative for succesfull market introduction and deployment of the AD systems!

https://www.currentresults.com/Weather/Europe/Cities/precipitation-annual-average.php The annual amount of precipitation is an average of historical weather data collected over a long period, in most cases 30 years.

FOG IS ALSO NOT RARE (E.G. IN THE US)

Annual averages for days with cloud or fog (major cities in the United States)

City	Cloud	Fog
Atlanta, Georgia	149	159
Austin, Texas	136	127
Baltimore, Maryland	152	144
Birmingham, Alabama	155	178
Boston, Massachusetts	164	139
Detroit, Michigan	185	156
Hartford, Connecticut	175	162
Houston, Texas	161	194
Indianapolis, Indiana	179	175

City	Cloud	Fog
Jacksonville, Florida	144	198
Kansas City, Missouri	149	123
Las Vegas, Nevada	73	5
Los Angeles, California	103	92
Louisville, Kentucky	171	142
Orlando, Florida	130	157
Philadelphia, Pennsylvania	160	164
Phoenix, Arizona	70	7
Pittsburgh, Pennsylvania	203	183

City	Cloud	Fog
Portland, Oregon	222	125
Providence, Rhode Island	164	166
Raleigh, North Carolina	149	198
Richmond, Virginia	160	185
Rochester, New York	200	133
Tampa, Florida	121	133
Virginia Beach, Virginia	153	157
Washington, DC	164	130

Fog in the US >100 days per year for major cities in US

Inclement weather is not a rare occurrence worldwide. It occurs particularly strongly and frequently at night.

!L3 System predictive detection & availability in bad weather is imperative for succesfull market introduction and deployment of the AD systems!

https://www.currentresults.com/Weather/Europe/Cities/precipitation-annual-average.php The annual amount of precipitation is an average of historical weather data collected over a long period, in most cases 30 years.

NEW UN REGULATION SINCE JAN. 2023: AUTOMATED LANE KEEPING SYSTEM MUST CONSIDER WEATHER

United Nations ECE/TRANS/WP.29/2022/59/Rev.1

Economic and Social Council

Distr.: General
30 May 2022

Original: English

Economic Commission for Europe

Inland Transport Committee

World Forum for Harmonization of Vehicle Regulations

187th session
Geneva, 21-24 June 2022
Item 4.8.2 of the provisional agenda
1958 Agreement:
Consideration of draft amendments to existing
UN Regulations submitted by GRVA

Proposal for the 01 series of amendments to UN Regulation No. 157 (Automated Lane Keeping Systems)

Submitted by the Working Party on Automated/Autonomous and Connected Vehicles*

5.2.3.2. The activated system shall adapt the vehicle speed to infrastructural and environmental conditions (e.G. Narrow curve radii, inclement weather)

"Automated lane keeping system (ALKS)" is a system which is activated by the driver and which keeps the vehicle within its lane for travelling speed of 130 km/h or less by controlling the lateral and longitudinal movements of the vehicle for extended periods without the need for further driver input.

2.1. "Operational design domain (ODD)" of the automated lane keeping system defines the specific operating conditions (e.G. Environmental, geographic, time-of-day, traffic, infrastructure, speed range, weather and other conditions) within the boundaries fixed by this regulation under which the automated lane keeping system is designed to operate without any intervention by the driver.

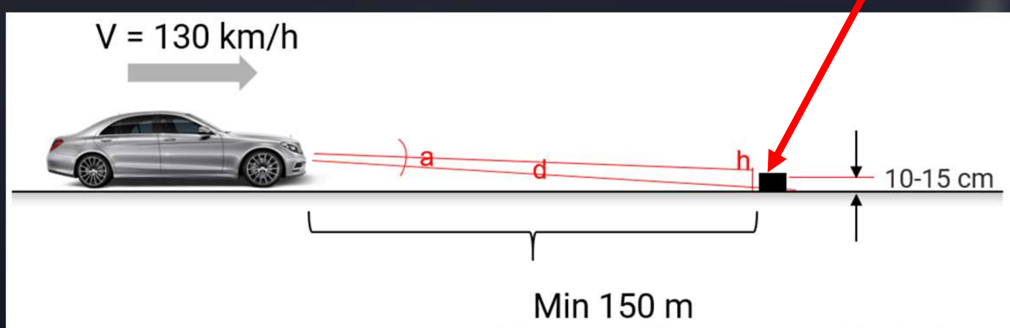
2.8 "operational design domain (ODD)" of the automated lane keeping system defines the specific operating conditions (e.G. Environmental, geographic, time-of-day, traffic, infrastructure, speed range, weather and other conditions)

2.9. "Operational design domain (ODD)" of the automated lane keeping system defines the specific operating conditions (e.G. Environmental, geographic, time-of-day, traffic, infrastructure, speed range, weather and other conditions) within the boundaries fixed by this regulation under which the automated lane keeping system is designed to operate without any intervention by the driver.

2.11. "Control strategy" means a strategy to ensure robust and safe operation of the function(s) of "the system" in response to a specific set of ambient and/or operating conditions (such as road surface condition, traffic intensity and other road users, adverse weather conditions, etc.). This may include the automatic deactivation of a function or temporary performance restrictions (e.G. A reduction in the maximum operating speed, etc.).

UN REGULATION EXTENDS AUTOMATED DRIVING UP TO 130 km/h IN CERTAIN CONDITIONS

- **Revised UNECE regulation R157 for automated lane keeping systems (ALKS) entered into force on 1 jan 2023 for all contracting countries (42).**
  - Allows OEMs to legally provide customers with ALKS (SAE Level 3 up to 130 km/h for "Minimum forward detection range")
  - "A passable object is such an object, **that may be driven over without causing an unreasonable risk** to the vehicle occupants or other road users regardless of whether the tyre of the ALKS vehicle comes in contact with the object or not."
  - **ALKS can *only* operate in conditions that allow bigger than "passable object" to be detected**



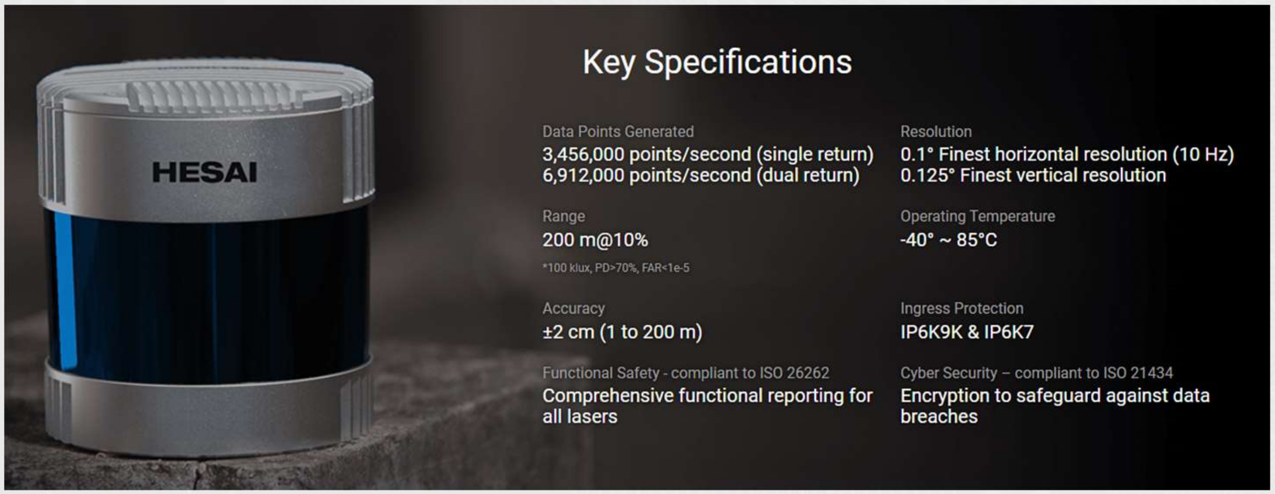
Specified maximum speed / km/h	*Minimum forward detection range / m*
0…60	46
70	50
80	60
90	75
100	90
110	110
120	130
130	150

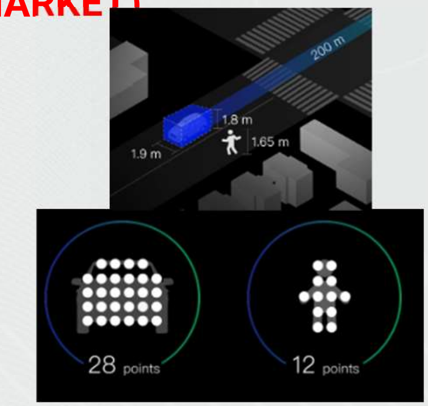
Min iFoV angle a= 0.15/150 = 1 mRAD (~0.057 degree)
- Challenging with current Lidar

Min iFoV angle a= 0.15/100 = 1.5 mRAD (~0.086 degree)
- Challenging with current Lidar

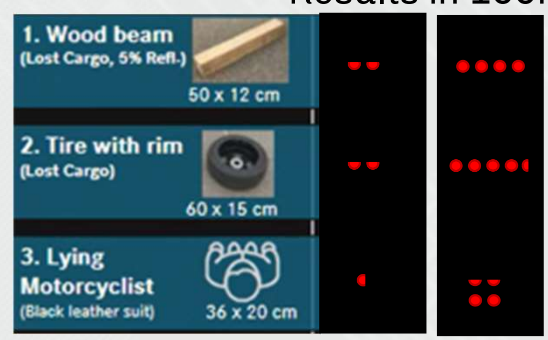
LIMITATIONS OF LIDAR

PANDAR 128 (128 CHANNELS) (CURRENTLY HIGHEST RESOLUTION ON MARKET)





Results in 150m



now future

3,456,000 points/sec= 345,600 points/per scan in contrast to 2.000.000 pixels with 10Hz of a GC (5,8 times more!)
0,1° ~ 0,26m Auflösung

Even if the resolution is doubled, the lost cargo cannot be reliably detected (minimum required improvement is factor 4). Traversability needs improvement of resolution > factor 6!

LOST CARGO PROBLEM AT NIGHT STILL UNSOLVED!

- **THE MAXIMUM SPEED AT WHICH AN ADS CAN TRAVEL IS LIMITED BY THE MAXIMUM RANGE OF DETECTION OF SMAL L OBSTACLES (SO-CALLED LOST CAGO, TYPICALLY TIRES 12 CM HIGH, MOTORCYCLIST 30 CM HIGH).**
- **FOR A DESIRED SPEED OF 130 KM/H, THE LOST CARGO MUST BE DETECTED AT A DISTANCE OF APPROX. 150 M. IF A DI STANCE OF ONLY 100M IS ACHIEVED, THE MAXIMUM SPEED DROPS TO 80 KM/H.**
- **CURRENTLY, THERE IS NO SERIES SENSOR INSTALLED IN THE VEHICLE WITH WHICH THIS PROBLEM CAN BE SOLVED!**
- **…BUT MAYBE SOON**

LOST CARGO CASE: HIGH END COLOR CAMERA VS. GATED CAMERA

LOW BEAM, TIRE IN 155 M DISTANCE, PEDESTRIANS IN 170 M DISTANCE CLEARLY VISIBLE !


High End Color-Camera with low beam headlights: Only the first 50m are visible

Gated Camera from BWV: The tire at 155m distance can be seen well!

LOST CARGO CASE: HIGH END COLOR CAMERA VS. GATED CAMERA

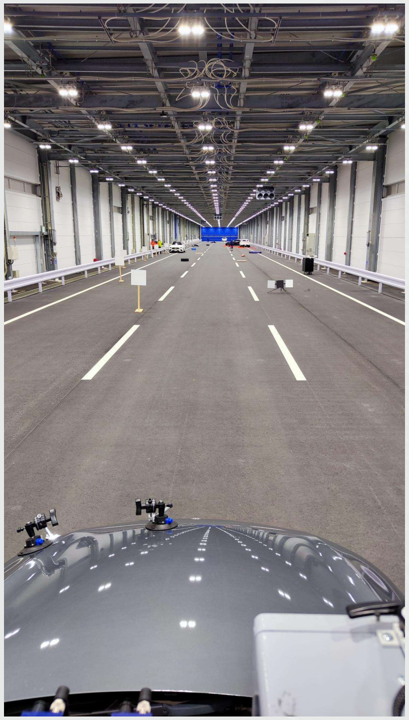
LOW BEAM, TIRE IN 155 M DISTANCE, PEDESTRIANS IN 170 M DISTANCE CLEARLY VISIBLE !

High End Color-Camera with low beam headlights : Only the first 50m are visible
OnSemi Aptina AR0230, resolution: 1920x1024

150 m

Gated Camera from BWV: The tire at 155m distance can be seen well!
Resolution – 800x480

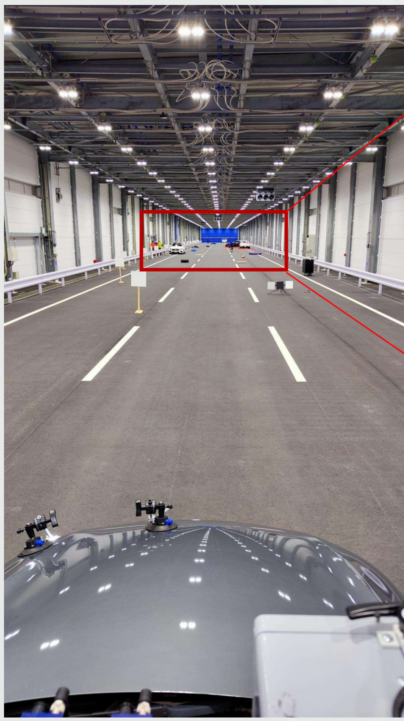
LOST CARGO MEASUREMENT CAMPAIGN IN THE JARI WEATHER CHAMBER



Test scenario for lost cargo distributed over 200 m weather chamber length.

Quiz: Where is the motorcyclist?

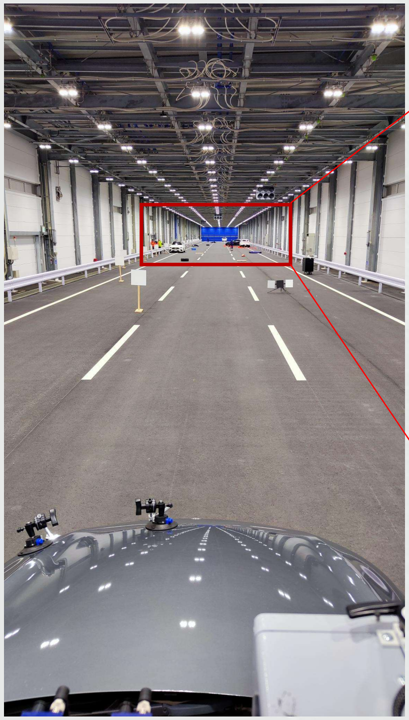
LOST CARGO MEASUREMENT CAMPAIGN IN THE JARI WEATHER CHAMBER



100,25	SQS white from the back
110,00	S-Classe blue from the side
110,00	Bumper
120,00	tire
160,00	motorcyclist
170,00	wooden bar
180,00	Pedestrian Standing dark blue
190,25	car Mistubishi

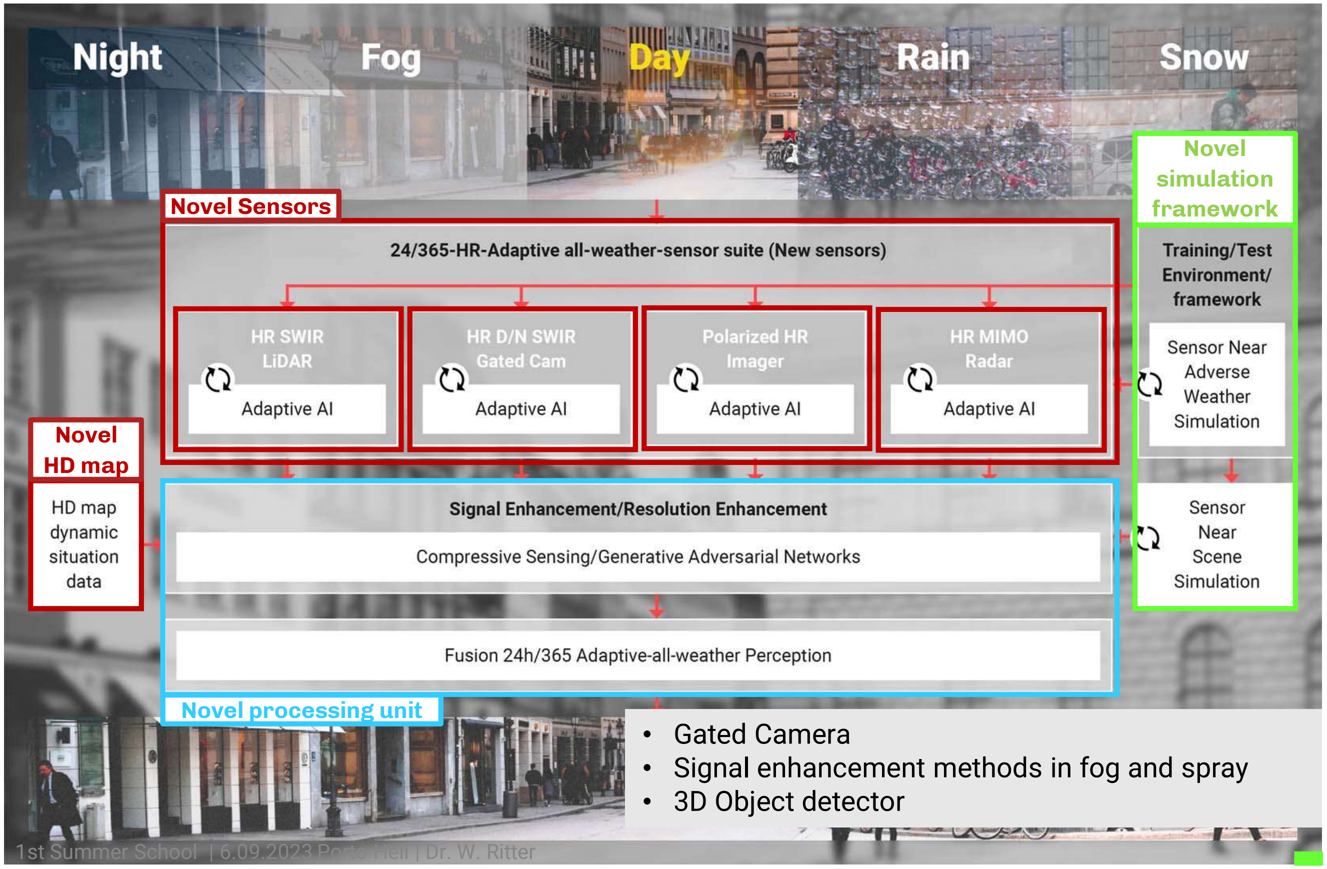
49,00	Palette
50,50	Tire
60,00	Bricks
70,00	Light Blue Doll laying perpendicular to car
70,00	Mercedes C-Klasse T
80,00	Exhaust
85,00	Plastic Box blue
87,50	Dark Blue Doll Standing looking in front to the car

A BIT HARDER: LOST CARGO > 75 M DISTANCE WITH FOG 80M VISIBILITY



Fog 80 m visibility range,

THE CONCEPT



- Gated Camera
- Signal enhancement methods in fog and spray
- 3D Object detector

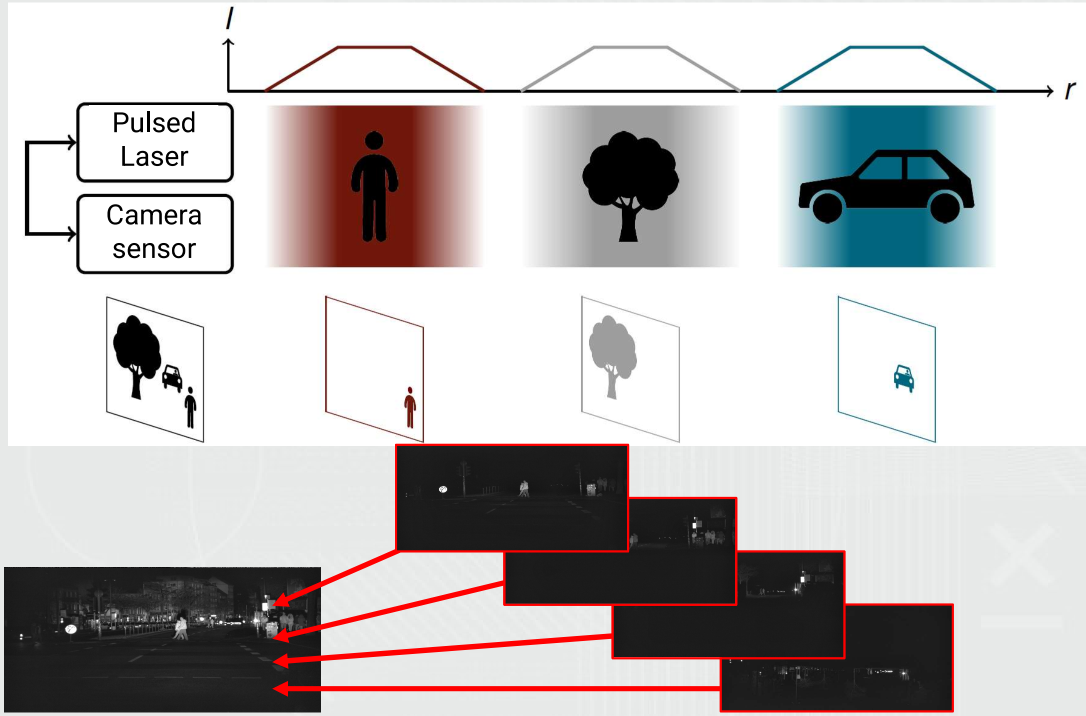
GATED CAMERA

ADVANTAGES OF A GATED CAMERA (COMPARED TO A STANDARD CAMERA)

Fog chamber scenario with a visibility of 50m.

THE GATED CAMERA DELIVERS USABLE IMAGES EVEN IN ADVERSE WEATHER CONDITIONS (EVEN W HEN NOTHING MORE CAN BE PERCEIVED WITH STANDARD CAMERAS OR STANDARD LIDARS.)

WHY IS THE IMAGE (ALMOST) OF A GATED CAMERA UNDISTURBED (BY AW)?



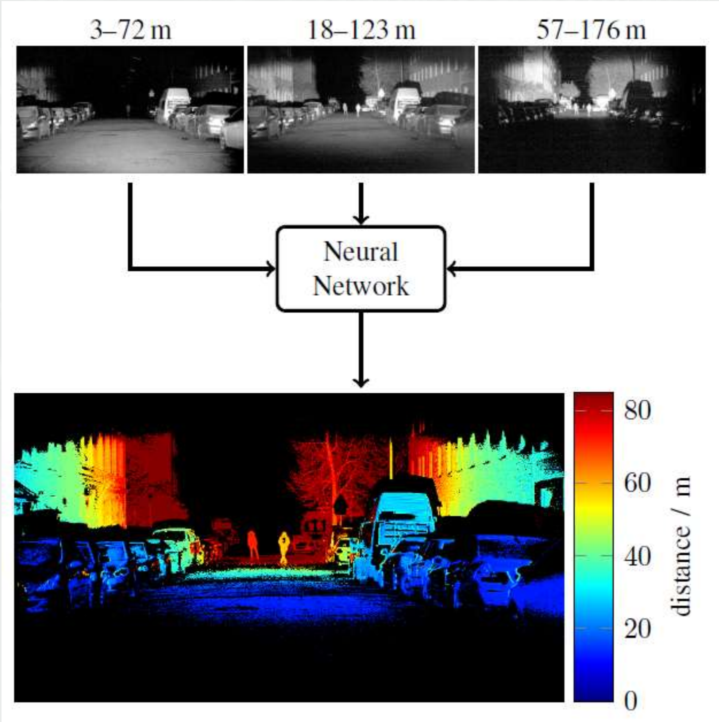
- With the gated camera various depth slices are illuminated and recorded. The result image is generated by adding up the depth slices.
- Why is the image (almost) undisturbed?
- Interference information (e.g. reflections on interfering particles such as snowflakes) outside of a depth range is not recorded and therefore does not interfere (overlay) the image information of interest

ADVANTAGES OF A GATED CAMERA (COMPARED TO A STANDARD CAMERA)

- Input: pixel intensities of three gated slices

[Grayvalue Slice 1 | Grayvalue Slice 2 | Grayvalue Slice 3]

- Output: Estimated depth
- Label: Lidar depth



A HIGH RESOLUTION DEPTH MAP (HERE 1280X720) WITH AN RELATIVE (TO THE DISTANCE) ACCURACY OF 5% CAN BE CALCULATED FROM THE DEPTH SLICES (*status 2020)

EXAMPLE VIDEO – DEPTH MAP 1280X720

T4.1 GATED DEPTH ESTIMATION (WORK FROM 2022)

LONG TERM GOAL (~2 YEARS):

Automatic adaption of gating parameters to environment conditions and combination of different depth cues (stereo, temporal, gated information) for accurate depth estimation

NEXT GOAL (~6 MONTHS):

- Long-range gated depth estimation with wide stereo sensor setup

WORK DONE:

Self-supervised gated depth estimation based on gated and temporal consistency (Gated2Gated)

Setting up stereo gated camera

Optimization of gating parameters for gated depth estimation

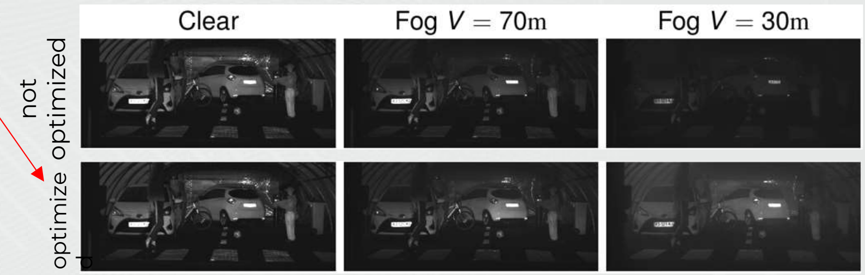


Fig. 3: Long term goal: Optimization of gating parameters to prevailing conditions

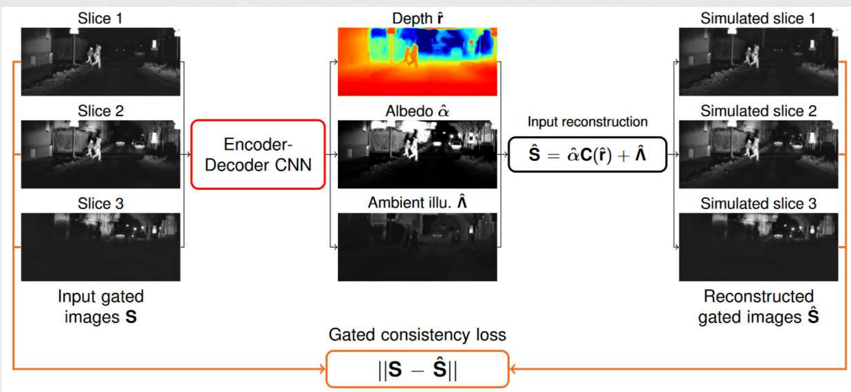


Fig. 1: Net-Architecture of self-supervised gated depth estimation.

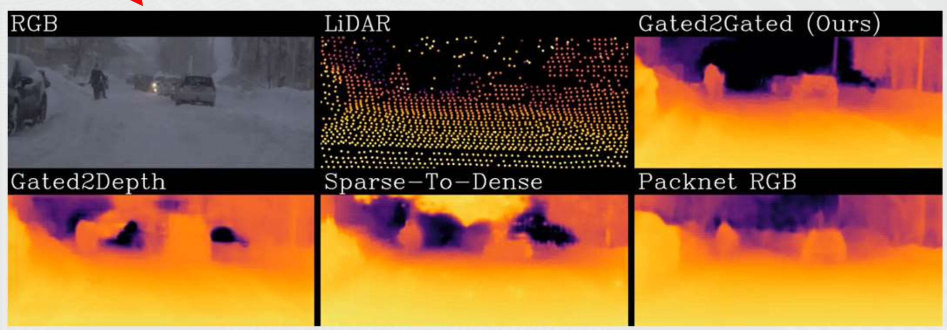


Fig. 2: Results of different depth estimation methods. The proposed Gated2Gated can handle snow much better than the other methods.

Paper CVPR2022: Gated2Gated: Self-Supervised Depth Estimation from Gated Images

T4.1 GATED STEREO DEPTH ESTIMATION

Long term goal (~2 years):

- Combination of different depth cues (gated, temporal, stereo) for high accuracy depth maps
- Adaptation of gating parameters to environment conditions and task

Short term goal and ongoing (~6 months):

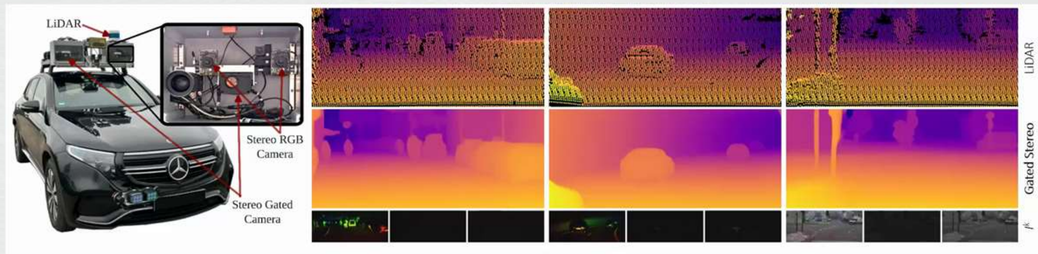
- Gated stereo depth estimation
- (Automatic optimizing gated parameters for prevailing conditions)

Completed work:

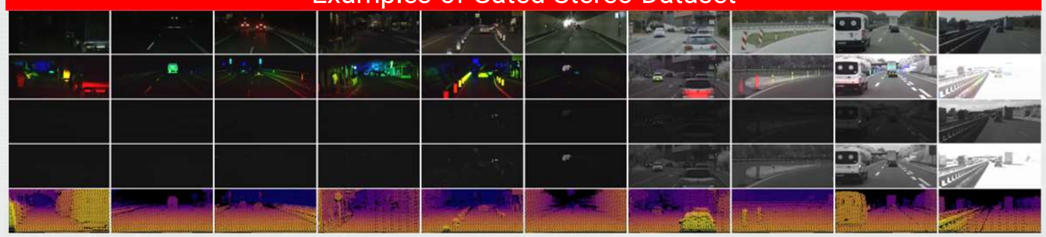
- Cooperation with Algolux & Princeton University for self-supervised depth estimation with temporal and gated consistency
- First collection campaigns for gated stereo data
- Optimization of gating parameters for depth estimation

- Gated Stereo achieves **50% better mean absolute depth error** than the next best method on stereo RGB images

Qualitative Results of Gated Stereo Depth Estimation*



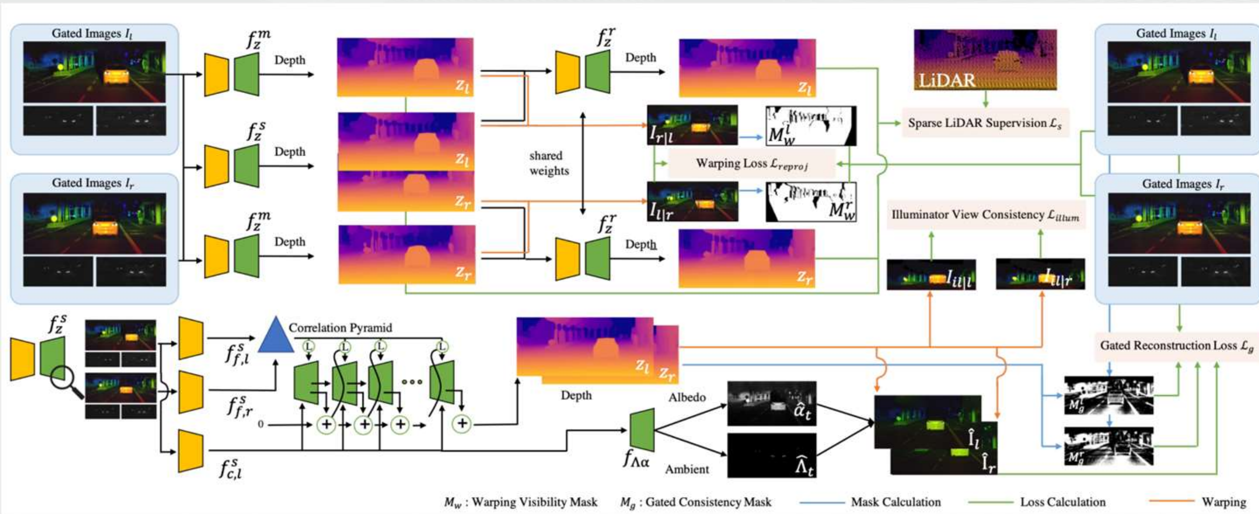
Examples of Gated Stereo Dataset



Significant step toward solving novel 3D vision tasks such as detecting small objects that are easy to miss, such as debris (lost cargo) at long distances, and detecting road edges and lanes in high quality.

* Paper CVPR2023: "Gated Stereo: Joint Depth Estimation from Gated and Wide-Baseline Active Stereo Cues"

GATED STEREO DEPTH ESTIMATION – HOW IT WORKS



Input:

- Stereo pair of three active gated images with time-of-flight information
- Stereo pair of two passive HDR-like captures for good performance in bright daylight conditions, where active cues have a low signal-to-noise ratio due to ambient illumination

Method:

- Network architecture consists of one monocular network per gated camera, a stereo network, and a fusion network where monocular and stereo depth predictions get fused
- Monocular network exploits depth-dependent gated intensity cues and stereo network relies on active stereo cues
- Network training relies on self-supervised losses that ensures consistency between different predicted outputs and sparse LiDAR ground truth supervision

Output:

- High-resolution dense depth maps

* Paper CVPR2023: “Gated Stereo: Joint Depth Estimation from Gated and Wide-Baseline Active Stereo Cues”

GATED STEREO DEPTH ESTIMATION – RESULTS

Take-away

- Gated Stereo uses three active and two additional high-dynamic range passive captures to perform robustly under bright daylight
- Gated Stereo generates high-resolution dense depth maps from multi-view/stereo cues and time-of-flight intensity cues
- Gated Stereo achieves **50% better mean absolute depth error** than the next best method on stereo RGB images

Quantitative Performance

Method	Modality	Night Performance					Day Performance				
		MAE	RMSE	δ1	δ2	δ3	MAE	RMSE	δ1	δ2	δ3
Gated Stereo	Stereo-Gated	**2.25**	**6.39**	**96.40**	**98.44**	**99.24**	**2.25**	**7.11**	**96.87**	**98.46**	**99.11**
RAFT-Stereo	Stereo-RGB	5.10	10.89	90.47	96.71	98.63	4.07	9.40	93.76	98.15	99.09
DepthFormer	Mono-RGB	6.20	12.15	85.18	95.76	98.47	5.06	10.59	90.65	97.46	99.02
Sparse2Dense	Mono-Sparse	5.22	9.97	87.06	95.77	98.20	4.77	10.05	88.06	96.57	98.63

Significant step toward solving novel 3D vision tasks such as detecting small objects that are easy to miss, such as debris (lost cargo) at long distances, and detecting road edges and lanes in high quality.

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SIGNAL ENHANCEMENT

T4.2 SIGNAL ENHANCEMENT

Long term goal (~2 years):
- Generic enhancement framework which can be used as pre-processing stage for object detection algorithms.

Next goal(~6 months):
- Extending camera methods to night time or to other modalities. Depending on available simulation methods.

Work done:
- Setting up single RGB camera enhancement algorithms with temporal, multi modal, multi view supervision for optimal image quality.

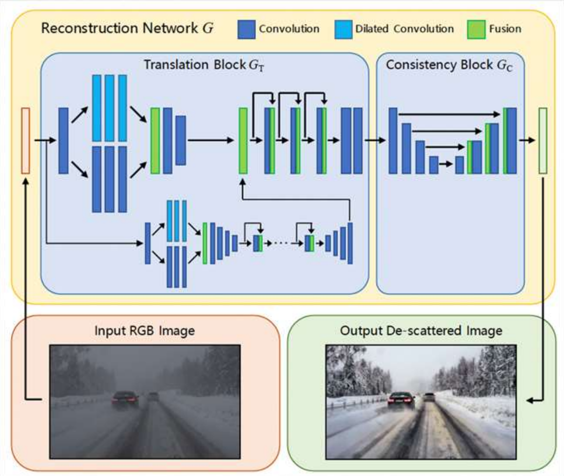


Fig 3. Network Architecture

Input (Heavy Snow)

Fig 1. Original Input Images

ZeroScatter Output

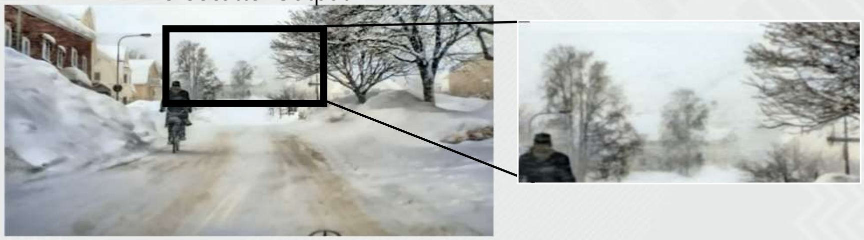


Fig. 2 Enhanced Camera Raw Data

Paper: ZeroScatter: Domain Transfer for Long Distance Imaging and Vision through Scattering Media. CVPR 2021

HAZED DATASET (IMAGE)

IMAGE HAZING ALGORITHM ADAPTED TO CITYSCAPES

REFINED STEREO DEPTHMAP THROUGH PSP-NET

KITTI IMAGES ARE TO BRIGHT AND THEREFORE UNREALISTIC FOG. BEFOREHAND APPLICATION OF CLAHE FOR A CO NTRAST ENHANCEMENT.

SIMULATED RAIN
(SIMPLIFIED SIMULATION, RAIN IS FALLING STRAIGHT DOWN)

Rain rate 5 mm/h

Rain rate 25 mm/h

Rain rate 50 mm/h

Rain rate 100 mm/h

Typical rain rates

100mm/h autumn downpour

300 mm/h tropical rain

SIMULATED SNOWFALL

(SIMPLIFIED SIMULATION, THE SNOW IS FALLING STRAIGT DOWN)

Snowfall rate 0,25 mm/h

Snowfall rate 0,5 mm/h

Snowfall rate 1,0 mm/h

Snowfall rate 2,5 mm/h

Typical snowfall rates:

SAE Snowfall rate for difficult flight operation 2,5 mm/h

Extreme rate up to 14 mm/h measured in USA.

LIDAR SIGNAL ENHANCEMENT

T4.2 IMPROVE LIDAR DETECTION IN ADVERSE WEATHER (E.G. WET ROAD, SPRAY)

Long term goal (~2 years):

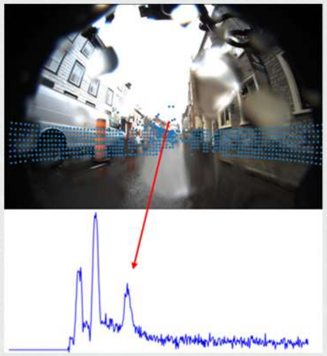
- Integrate temporal information over multiple frames into detectors to mitigate erroneous detections in adverse weather conditions

Short term goal and Ongoing (~6 months):

- Simulate and/or collect raw LiDAR data in adverse weather scenarios
- Improve object detection with raw LiDAR data

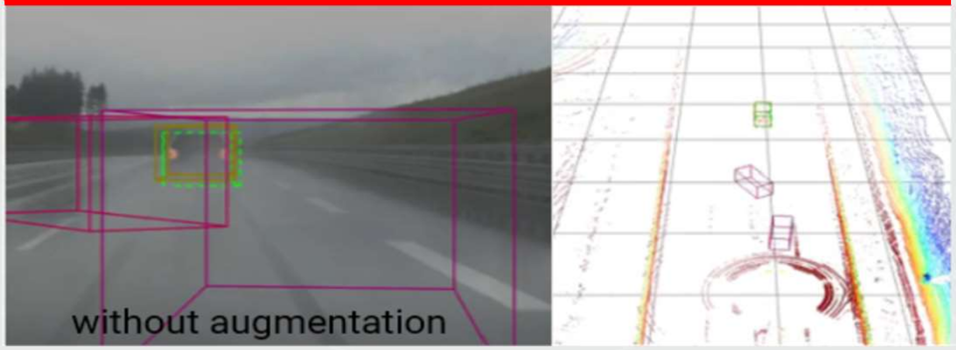
Completed Work:

- Cooperation with TU Darmstadt for augmenting spray and wet road effects for LiDAR point clouds based on physical models
- Improve LiDAR based detectors by using augmented training data and evaluate on a dataset with real spray

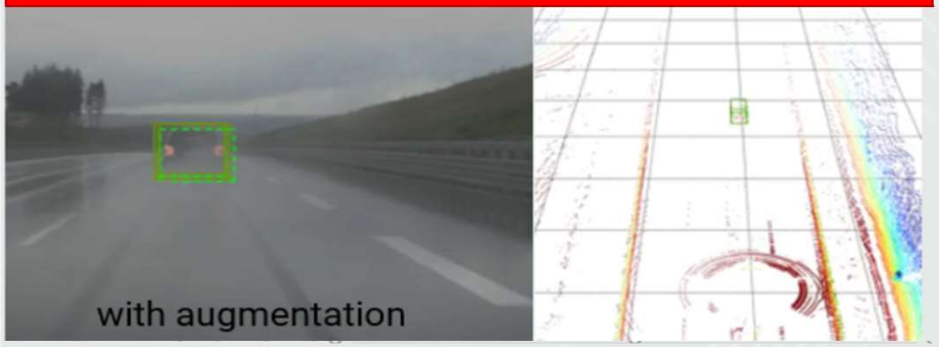


Disturbed raw LiDAR signal during rain: Strongest peak from e.g. rain drop, fog etc. Object echo is behind strongest echo

Without augmentation



With augmentation



Detection RATE improvement of up to 17% with significant less false detections and a far better object localization

For more details see publication submitted to IEEE Sensors Journal in 2022: Simulating Road Spray in Lidar Sensor Models: Clemens Linnhoff, Dominik Scheuble, Mario Bijelic, Lukas Elster, Philipp Rosenberger, Werner Ritter, Dengxin Dai and Hermann Winner

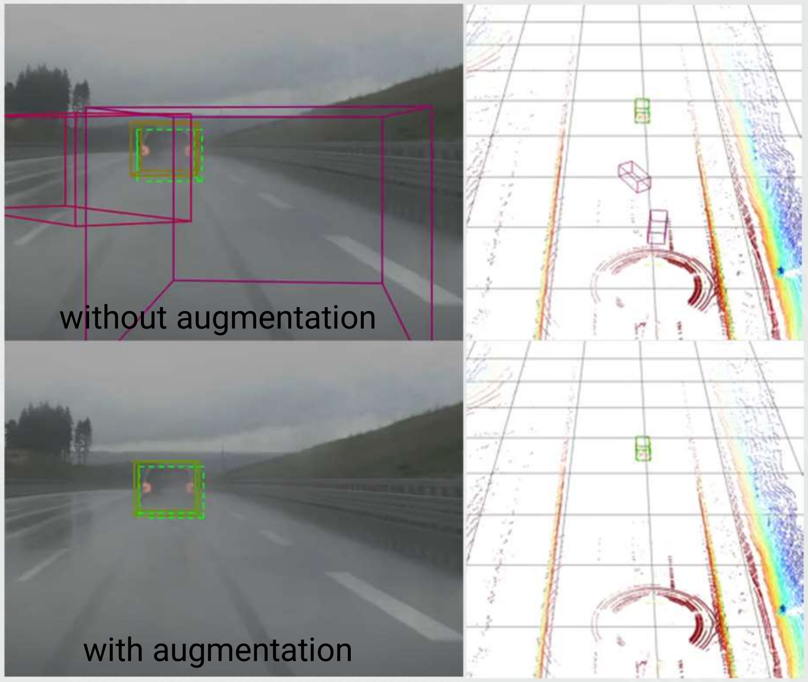
RESULTS

Take-away

- Augmentation boosts performance in spray significantly
- Augmentation does not lead to sacrifices on clear-weather performance
- Related adverse weather simulations do not generalize well to spray

Average Precision (AP) for PV-RCNN [1]

	spray test set			clear-weather test set		
	0-50	0-30	30-50	0-50	0-30	30-50
Spray aug.	**75.36**	**81.74**	**67.02**	58.90	71.69	**44.06**
No aug.	57.97	69.75	42.11	58.23	71.33	42.54
Rain aug.	67.71	75.82	55.05	**59.23**	**71.77**	43.88
Fog aug.	43.32	59.07	21.25	58.59	71.73	42.40



[1] Shi et al, Pv-rcnn: Point-voxel feature set abstraction for 3d object detection, 2020

Detection RATE improvement of up to 17% with significant less false detections and a far better object localization!

END-TO-END LIDAR HYPERPARAMETER OPTIMIZATION

Long term goal (~2 years):

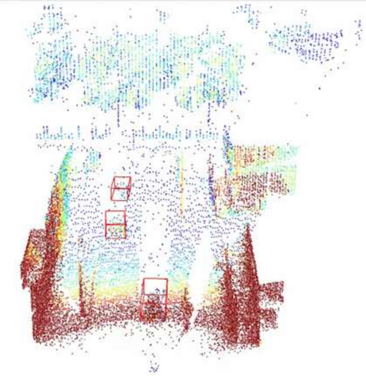
- Automatically optimize LiDAR detection across the entire process path from raw signal to detection via Deep Neural Networks to environmental conditions (from clear view to adverse weather).

Short term goal and Ongoing (~6 months):

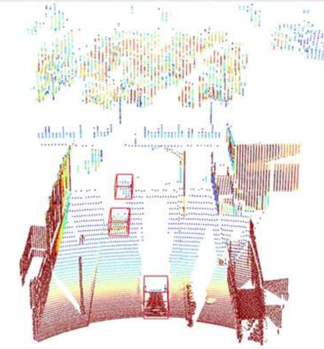
- Application to a real / full wavefront lidar

Completed Work:

- CARLA simulation environment that can extract full wavefront data and process in a DSP model
- Development of 0-th order multi-objective (MOO) optimizer for finding optimal DSP parameters
- Optimizing DSP parameters beats manual expert-tuning
- Object detection on an End-to-End optimized point cloud with object detection (AP for cars and pedestrians) **outperforms expert-tuning by 39.5% AP**.



expert-tuned

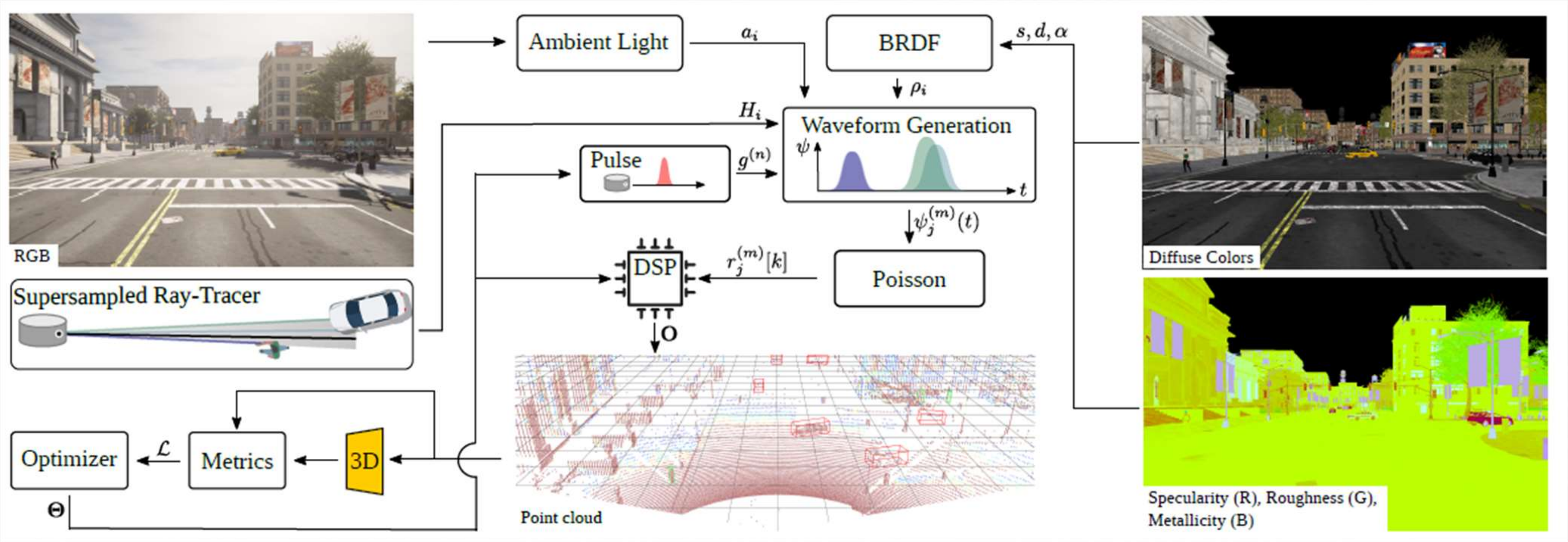


optimized

Comparison of expert-tuned (upper) and optimized (lower) DSP. Tuning parameters by hand is difficult and tedious due to large and non-linear parameter space. Optimizing DSP parameters generates clearer point clouds and improves object detection

For more details see Paper CVPR2023: “LiDAR-in-the-loop Hyperparameter Optimization”

END-TO-END LIDAR HYPERPARAMETER OPTIMIZATION



LiDAR Simulation Method. We propose a parameterizable LiDAR simulation model that generates full transient waveforms by extracting scene response H, ambient light a and object reflectances s, d, a from CARLA. The optimized vector T includes both pulse and DSP hyperparameters. Wavefronts are processed by the DSP, resulting in a point cloud O. We "close the loop" by feeding O to 3D object detection and depth estimation methods that define loss functions L when evaluated on validation datasets. These end-to-end loss functions drive an MOO solver which converges to optimal parameters

For more details see Paper CVPR2023: "LiDAR-in-the-loop Hyperparameter Optimization"

RGB IMAGE SIGNAL ENHANCEMENT

T4.3 PHYSICALLY-BASED INVERSE NEURAL RENDERING TO REMOVE FOG

Long term goal (~2 years):

- Determine from RGB-sequences airlight, clear scene sequence, fog density, pixel-wise depth and other components (e.g. albedo, reflectance, illumination).
- Extend this approach to different sensors modalities (e.g. Gated images, LiDAR)

Next goal(~6 months):

- Extend physics-based scene representation approach to multiple settings and modalities.

Work done:

- Given a RGB sequence, separate the fog by learning a disjoint representation of clear scene and scattering medium, through the imposition of physics-based constrains.

Fig. 1: Example of reconstructed scene (original, defogged and depth)

NEW! Based only on RGB image sequences and physics knowledge about the image formation, this approach automatically determines the image components like clear image, fog, color, depth, albedo, ...

Paper: ScatterNeRF: Seeing Through Fog with Physically-Based Inverse Neural Rendering. Submitted to ICCV 2023

METHOD: PROBLEM FORMULATION

Main ideas:

- Employ a Neural Radiance Field algorithm, but model Fog and Scene separately
- Use physics-based losses to enforce this division

$$C(r)_F = \int_{t_n}^{t_f} T_c(t) \underbrace{\left(T_p(t)\sigma_p(r(t))c_p(r(t))\right)}_{\text{Clear Scene contribution}} + T_p(t)\underbrace{\left(T_c(t)\sigma_c(r(t))c_c(r(t))\right)}_{\text{Fog contribution}} \, dt$$

$$L_A = E_r\left[\left|\hat{c}_p(r) - \bar{c}_p(r)\right|_2^2\right]$$

$$L_{eF} = E_r\left[\sum_i \tilde{\alpha}_{F_i}(r) \cdot \log\left(\tilde{\alpha}_{F_i}(r)\right)\right]$$

$$L_{depth} = E_r\left[\left|\widehat{D}_c(r) - \bar{D}_c(r)\right|_2^2\right]$$

$$L_{ec} = E_r\left[-\sum_i \widehat{w}_{c_i}(r) \cdot \log\left(\widehat{w}_{c_i}(r)\right)\right]$$

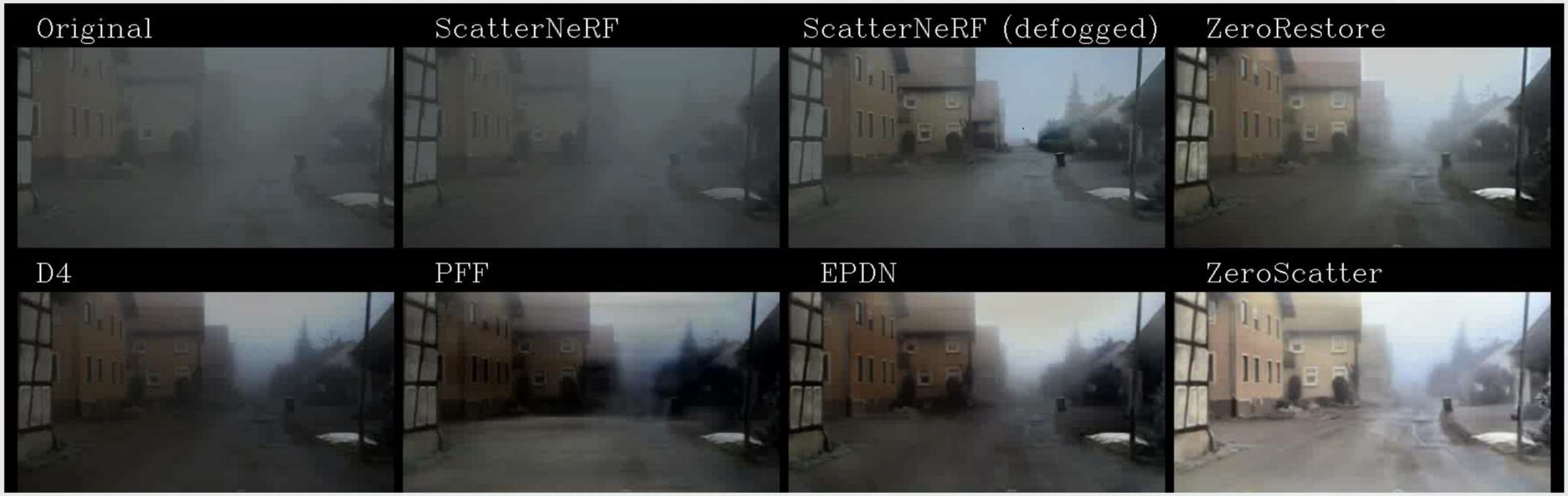
$$L_{tot} = \underbrace{L_{rgb}}_{\text{reconstruction loss}} + \underbrace{L_A}_{\text{airlight loss}} + \underbrace{L_{depth}}_{\text{depth loss}} + \underbrace{L_{ec} + L_{eF}}_{\text{entropy loss}}$$

entropy loss
c clear scene, F fog

Paper: ScatterNeRF: Seeing Through Fog with Physically-Based Inverse Neural Rendering. Submitted to ICCV 2023

T4.3 PHYSICALLY-BASED INVERSE NEURAL RENDERING TO REMOVE FOG –

COMPARISON: DEFOGGING VIDEO



Comparison of proposed method (ScatterNeRF) against state-of-the-art image descattering algorithms

ScatterNeRF provides higher contrast and stronger contours and colors compared to other previous state-of-the-art defogging methods.

T4.3 PHYSICALLY-BASED INVERSE NEURAL RENDERING TO REMOVE FOG

OTHER RESULTS : MODIFICATION FOG DENSITY

Example of re-rendered scenes with varying fog densities

T4.3 PHYSICALLY-BASED INVERSE NEURAL RENDERING TO REMOVE FOG

OTHER RESULTS : FOG CHAMBER

Example result of sequence collected in a controlled environment (JARI fog chamber)

SCENE UNDERSTANDING – 3D OBJECT DETECTION IN ADVERSE WEATHER

T4.4 SCENE UNDERSTANDING – 3D OBJECT DETECTION IN ADVERSE WEATHER

Long term goal (~2 years):
- 3D Object detection methods for the defined use cases with the possibility of multi modal fusion and seamless integration of enhancement methods with a backloop adaptation.

Next goal(~6 months):
- Extending single sensing methods to temporal fusion.
- Possibility to use enhancement stage as algorithmic input.

Work done:
- Setting up single 3D object detection methods for single modalities.

Fig 1. Gated3D used for 3D Detection of Obstacles in adverse weather

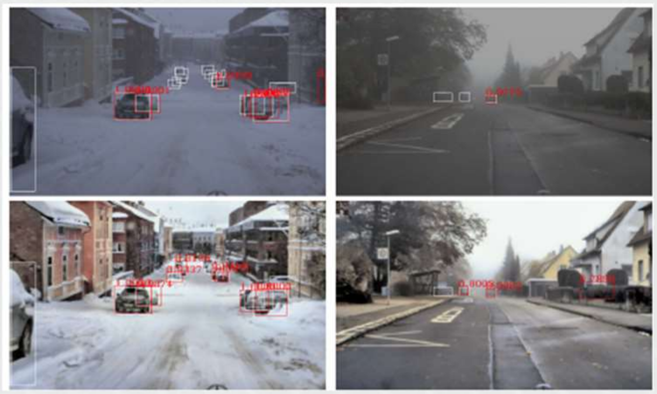


Fig 3. Enhanced Camera Detections

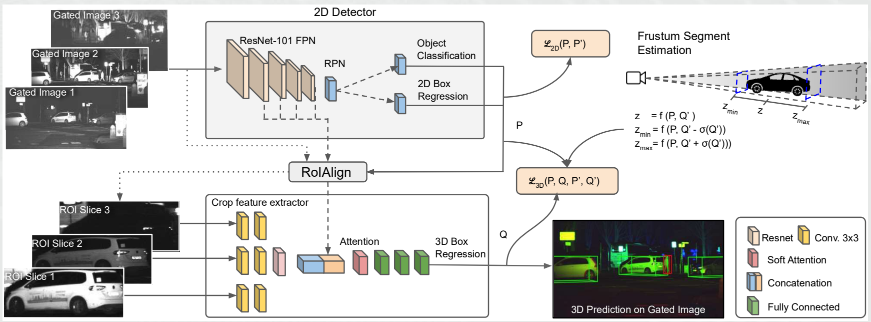


Fig. 2. Gated3D Architecture

Paper: Gated3D: Monocular 3D Object Detection From Temporal Illumination Cues. ICCV 2021

3D-OBSTACLE DETECTION IN ADVERSE WEATHER … ONE MORE EXAMPLE

THANK YOU VERY MUCH

FOR YOUR ATTENTION!

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