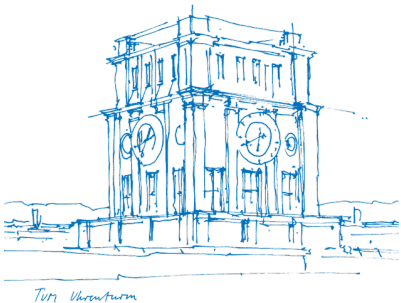
Associate Professorship of Embedded Systems and Internet of Things
TUM School of Computation, Information and Technology
Technical University of Munich

Perspective-Shift Attacks Against Optical Perception Sensors: A Novel Attack Vector on LiDAR and Camera

Marco Calipari*, Michael Kühr*, Dominik Kulmer, Maximilian Luedecke, Mohammad Hamad, Sebastian Steinhorst

Associate Professorship of Embedded Systems and Internet of Things
TUM School of Computation, Information and Technology
Technical University of Munich

August 11th, 2026

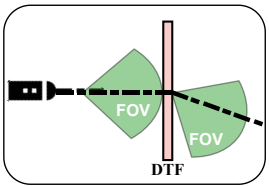


What are Perspective Shift Attacks?

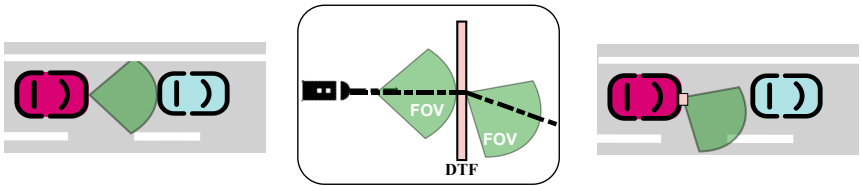


What are Perspective Shift Attacks?



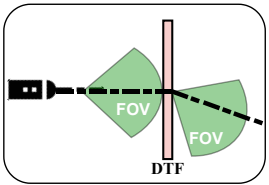


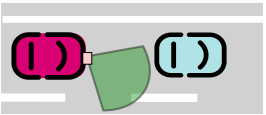
What are Perspective Shift Attacks?

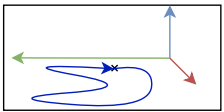


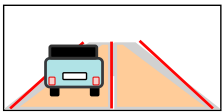
What are Perspective Shift Attacks?



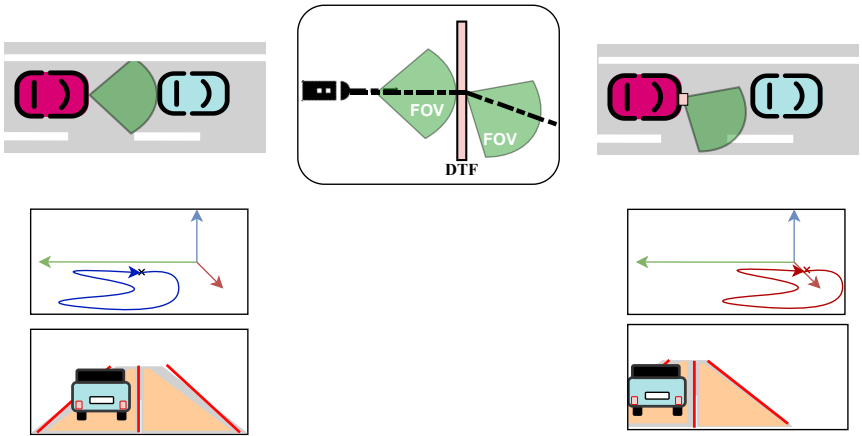








What are Perspective Shift Attacks?



Content

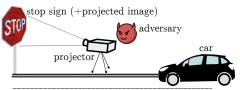
1. Background
2. Threat Model
3. Digital Attack Simulation
4. Physical Evaluation
5. Attack Detection
6. Conclusion

Background

- Physical Attacks on Optical Perception Sensors:
  - Camera: Patches, Projections, Light, ...



RP_2, Eykholt *et al.*, CVPR 2018



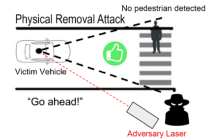
SLAP, Lovisotto *et al.*, USENIX 2021



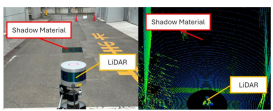
ILR, Sato *et al.*, NDSS 2024

Background

- Physical Attacks on Optical Perception Sensors:
  - Camera: Patches, Projections, Light, . . .
  - LiDAR: Light, Objects, . . .



You Can't See Me, Cao *et al.*, USENIX 2023



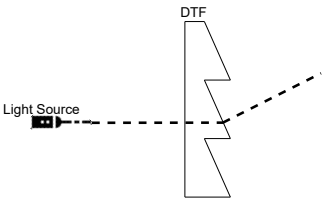
Invisible but Detected, Kobayashi *et al.*, USENIX 2025

Background

- Physical Attacks on Optical Perception Sensors:
  - Camera: Patches, Projections, Light, ...
  - LiDAR: Light, Objects, ...
- Attacks against: SLAM, Detection, Classification, ...

Background

- Physical Attacks on Optical Perception Sensors:
  - Camera: Patches, Projections, Light, ...
  - LiDAR: Light, Objects, ...
- Attacks against: SLAM, Detection, Classification, ...
- Direction Turning Film[a]
  - Used for illumination scenarios
  - Microprisms in a polycarbonate sheet



[a] https://luminitco.com/prismatics-by-luminit/direction-turning-film/

Background – Field of View of Optical Perception Sensors

- An optical perception sensors observes only a limited portion of the environment
  $\rightarrow$ Field of View (FoV)

Background – Field of View of Optical Perception Sensors

- An optical perception sensors observes only a limited portion of the environment
  $\rightarrow$ Field of View (FoV)
- Tuple of horizontal and vertical angular intervals: $\mathrm{FoV}_{\mathrm{OPS}} := (H_{\mathrm{FoV}}, V_{\mathrm{FoV}})$

Background – Field of View of Optical Perception Sensors

- An optical perception sensors observes only a limited portion of the environment
  $\rightarrow$ Field of View (FoV)
- Tuple of horizontal and vertical angular intervals: $\mathrm{FoV}_{\mathrm{OPS}} := (H_{\mathrm{FoV}}, V_{\mathrm{FoV}})$
- Constrained by technical specifications: $H_{\mathrm{FoV}} = [\theta_{\min}, \theta_{\max}], \quad V_{\mathrm{FoV}} = [\varphi_{\min}, \varphi_{\max}]$

Background – Field of View of Optical Perception Sensors

- An optical perception sensors observes only a limited portion of the environment
  $\rightarrow$ Field of View (FoV)
- Tuple of horizontal and vertical angular intervals: $\mathrm{FoV}_{\mathrm{OPS}} := (H_{\mathrm{FoV}}, V_{\mathrm{FoV}})$
- Constrained by technical specifications: $H_{\mathrm{FoV}} = [\theta_{\min}, \theta_{\max}], \quad V_{\mathrm{FoV}} = [\varphi_{\min}, \varphi_{\max}]$
- Finite subset of the environment: $\varepsilon^* = \{p \in \varepsilon \mid \theta(p) \in H_{\mathrm{FoV}} \ \wedge \ \varphi(p) \in V_{\mathrm{FoV}}\}$

Background – Field of View of Optical Perception Sensors

- An optical perception sensors observes only a limited portion of the environment
  $\rightarrow$ Field of View (FoV)
- Tuple of horizontal and vertical angular intervals: $\mathrm{FoV}_{\mathrm{OPS}} := (H_{\mathrm{FoV}}, V_{\mathrm{FoV}})$
- Constrained by technical specifications: $H_{\mathrm{FoV}} = [\theta_{\min}, \theta_{\max}], \quad V_{\mathrm{FoV}} = [\varphi_{\min}, \varphi_{\max}]$
- Finite subset of the environment: $\varepsilon^* = \{p \in \varepsilon \mid \theta(p) \in H_{\mathrm{FoV}} \ \wedge \ \varphi(p) \in V_{\mathrm{FoV}}\}$
- Sensor output is based on this subset: $x = \mathcal{S}(\varepsilon^*)$

Threat Model – Goal and Characteristics

- Targeting LiDARs and cameras

Threat Model – Goal and Characteristics

- Targeting LiDARs and cameras
- Change the FoV instead of the environment $\rightarrow$ Introduce Δ_{PSA}

Threat Model – Goal and Characteristics

- Targeting LiDARs and cameras
- Change the FoV instead of the environment → Introduce Δ_{PSA}
  - $H_{\mathrm{FoV,PSA}} = [\theta_{\min} + \Delta_{\mathrm{PSA}}, \theta_{\max} + \Delta_{\mathrm{PSA}}]$
  - $V_{\mathrm{FoV,PSA}} = [\varphi_{\min} + \Delta_{\mathrm{PSA}}, \varphi_{\max} + \Delta_{\mathrm{PSA}}]$

Threat Model – Goal and Characteristics

- Targeting LiDARs and cameras
- Change the FoV instead of the environment $\rightarrow$ Introduce Δ_{PSA}
  - $H_{\mathrm{FoV,PSA}} = [\theta_{\min} + \Delta_{\mathrm{PSA}}, \theta_{\max} + \Delta_{\mathrm{PSA}}]$
  - $V_{\mathrm{FoV,PSA}} = [\varphi_{\min} + \Delta_{\mathrm{PSA}}, \varphi_{\max} + \Delta_{\mathrm{PSA}}]$
  - Affects subset of perceived environment and the sensor output

Threat Model – Goal and Characteristics

- Targeting LiDARs and cameras
- Change the FoV instead of the environment → Introduce Δ_{PSA}
  - $H_{\mathrm{FoV,PSA}} = [\theta_{\min} + \Delta_{\mathrm{PSA}}, \theta_{\max} + \Delta_{\mathrm{PSA}}]$
  - $V_{\mathrm{FoV,PSA}} = [\varphi_{\min} + \Delta_{\mathrm{PSA}}, \varphi_{\max} + \Delta_{\mathrm{PSA}}]$
  - Affects subset of perceived environment and the sensor output
  - Change of FoV through optical film on the sensor

Threat Model – Goal and Characteristics

- Targeting LiDARs and cameras
- Change the FoV instead of the environment → Introduce Δ_{PSA}
  - $H_{\mathrm{FoV,PSA}} = [\theta_{\min} + \Delta_{\mathrm{PSA}}, \theta_{\max} + \Delta_{\mathrm{PSA}}]$
  - $V_{\mathrm{FoV,PSA}} = [\varphi_{\min} + \Delta_{\mathrm{PSA}}, \varphi_{\max} + \Delta_{\mathrm{PSA}}]$
  - Affects subset of perceived environment and the sensor output
  - Change of FoV through optical film on the sensor
- Characteristics:

Threat Model – Goal and Characteristics

- Targeting LiDARs and cameras
- Change the FoV instead of the environment $\rightarrow$ Introduce Δ_{PSA}
  - $H_{\mathrm{FoV,PSA}} = [\theta_{\min} + \Delta_{\mathrm{PSA}}, \theta_{\max} + \Delta_{\mathrm{PSA}}]$
  - $V_{\mathrm{FoV,PSA}} = [\varphi_{\min} + \Delta_{\mathrm{PSA}}, \varphi_{\max} + \Delta_{\mathrm{PSA}}]$
  - Affects subset of perceived environment and the sensor output
  - Change of FoV through optical film on the sensor
- Characteristics:
  - Stealthiness: Inconspicuous transparent film on the sensor

Threat Model – Goal and Characteristics

- Targeting LiDARs and cameras
- Change the FoV instead of the environment → Introduce Δ_{PSA}
  - $H_{\mathrm{FoV,PSA}} = [\theta_{\min} + \Delta_{\mathrm{PSA}}, \theta_{\max} + \Delta_{\mathrm{PSA}}]$
  - $V_{\mathrm{FoV,PSA}} = [\varphi_{\min} + \Delta_{\mathrm{PSA}}, \varphi_{\max} + \Delta_{\mathrm{PSA}}]$
  - Affects subset of perceived environment and the sensor output
  - Change of FoV through optical film on the sensor
- Characteristics:
  - Stealthiness: Inconspicuous transparent film on the sensor
  - Limited one-time physical access to sensor

Threat Model – Goal and Characteristics

- Targeting LiDARs and cameras
- Change the FoV instead of the environment → Introduce Δ_{PSA}
  - $H_{\mathrm{FoV,PSA}} = [\theta_{\min} + \Delta_{\mathrm{PSA}}, \theta_{\max} + \Delta_{\mathrm{PSA}}]$
  - $V_{\mathrm{FoV,PSA}} = [\varphi_{\min} + \Delta_{\mathrm{PSA}}, \varphi_{\max} + \Delta_{\mathrm{PSA}}]$
  - Affects subset of perceived environment and the sensor output
  - Change of FoV through optical film on the sensor
- Characteristics:
  - Stealthiness: Inconspicuous transparent film on the sensor
  - Limited one-time physical access to sensor
  - Controlled Target

Threat Model – Goal and Characteristics

- Targeting LiDARs and cameras
- Change the FoV instead of the environment $\rightarrow$ Introduce Δ_{PSA}
  - $H_{\mathrm{FoV,PSA}} = [\theta_{\min} + \Delta_{\mathrm{PSA}}, \theta_{\max} + \Delta_{\mathrm{PSA}}]$
  - $V_{\mathrm{FoV,PSA}} = [\varphi_{\min} + \Delta_{\mathrm{PSA}}, \varphi_{\max} + \Delta_{\mathrm{PSA}}]$
  - Affects subset of perceived environment and the sensor output
  - Change of FoV through optical film on the sensor
- Characteristics:
  - Stealthiness: Inconspicuous transparent film on the sensor
  - Limited one-time physical access to sensor
  - Controlled Target
  - Minor adversarial impact on perception $\rightarrow$ Change FoV, not environment

Threat Model – Goal and Characteristics

- Targeting LiDARs and cameras
- Change the FoV instead of the environment → Introduce Δ_{PSA}
  - $H_{\mathrm{FoV,PSA}} = [\theta_{\min} + \Delta_{\mathrm{PSA}}, \theta_{\max} + \Delta_{\mathrm{PSA}}]$
  - $V_{\mathrm{FoV,PSA}} = [\varphi_{\min} + \Delta_{\mathrm{PSA}}, \varphi_{\max} + \Delta_{\mathrm{PSA}}]$
  - Affects subset of perceived environment and the sensor output
  - Change of FoV through optical film on the sensor
- Characteristics:
  - Stealthiness: Inconspicuous transparent film on the sensor
  - Limited one-time physical access to sensor
  - Controlled Target
  - Minor adversarial impact on perception → Change FoV, not environment
  - Illumination-independent multimodal attack

Threat Model – Knowledge and Capabilities

- No prior knowledge of perception modules $\rightarrow$ black-box attack

Threat Model – Knowledge and Capabilities

- No prior knowledge of perception modules $\rightarrow$ black-box attack
- One-time physical access to target vehicle

Threat Model – Knowledge and Capabilities

- No prior knowledge of perception modules $\rightarrow$ black-box attack
- One-time physical access to target vehicle
- Minimum system knowledge $\rightarrow$ Only position of the sensors

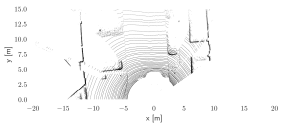
Threat Model – Knowledge and Capabilities

- No prior knowledge of perception modules $\rightarrow$ black-box attack
- One-time physical access to target vehicle
- Minimum system knowledge $\rightarrow$ Only position of the sensors
- Enough material to cover the sensor area

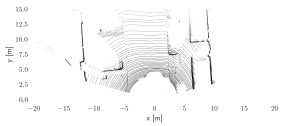
Digital Attack Simulation

How does a changed FoV affect the LiDAR?

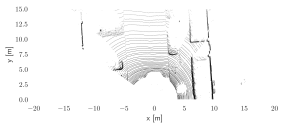
- Horizontal FoV shift of 20° on KITTI data
- Evaluate impact of pose estimation with KITTI odometry sequences and KISS-ICP



FoV left shift



Benign FoV

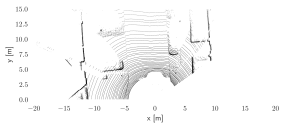


FoV right shift

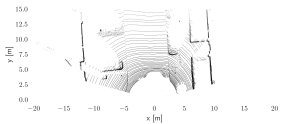
Digital Attack Simulation

How does a changed FoV affect the LiDAR?

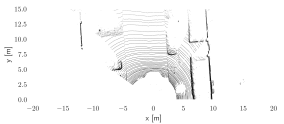
- Horizontal FoV shift of 20° on KITTI data
- Evaluate impact of pose estimation with KITTI odometry sequences and KISS-ICP
- Result:
  - Sequences with turning maneuvers show higher displacement
  - KISS-ICP's optimization is very robust if features are consistent



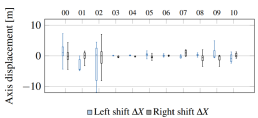
FoV left shift



Benign FoV



FoV right shift

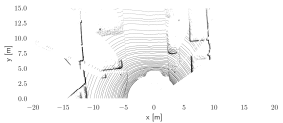


Displacement

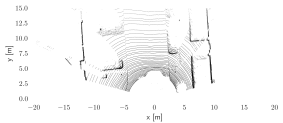
Digital Attack Simulation

How does a changed FoV affect the LiDAR?

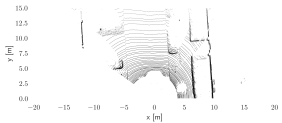
- Horizontal FoV shift of 20° on KITTI data
- Evaluate impact of pose estimation with KITTI odometry sequences and KISS-ICP
- Result:
  - Sequences with turning maneuvers show higher displacement
  - KISS-ICP's optimization is very robust if features are consistent
- It is possible to attack LiDARs!



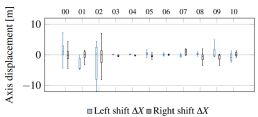
FoV left shift



Benign FoV



FoV right shift



Displacement

Digital Attack Simulation

How does a changed FoV affect the camera?

- Capture dual-fisheye spherical images
- Curvilinear projection of the FoV and a horizontal shift of 20°

Digital Attack Simulation

How does a changed FoV affect the camera?

- Capture dual-fisheye spherical images
- Curvilinear projection of the FoV and a horizontal shift of 20°
- Result of lane detection:
  - Lanes are still detected
  - Shift of vanishing point



FoV left shift



Benign FoV



FoV right shift

Digital Attack Simulation

How does a changed FoV affect the camera?

- Capture dual-fisheye spherical images
- Curvilinear projection of the FoV and a horizontal shift of 20°
- Result of lane detection:
  - Lanes are still detected
  - Shift of vanishing point
- It is possible to attack cameras!



FoV left shift



Benign FoV



FoV right shift

Physical Evaluation – Static Physical Tests

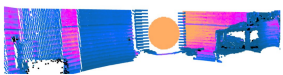
- Goal: Demonstrate physical feasibility of PSAs
- Static indoor setup in a controlled environment with DTF placed on the sensor

Physical Evaluation – Static Physical Tests

- Goal: Demonstrate physical feasibility of PSAs
- Static indoor setup in a controlled environment with DTF placed on the sensor
  - LiDAR: Ouster OS1
  - Traffic sign with high reflectivity

Physical Evaluation – Static Physical Tests

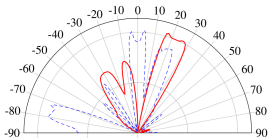
- Goal: Demonstrate physical feasibility of PSAs
- Static indoor setup in a controlled environment with DTF placed on the sensor
  - LiDAR: Ouster OS1
  - Traffic sign with high reflectivity



Benign



DTF-based PSA

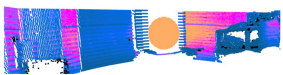


Normalized reflectivity

Physical Evaluation – Static Physical Tests

- Goal: Demonstrate physical feasibility of PSAs
- Static indoor setup in a controlled environment with DTF placed on the sensor
  - LiDAR: Ouster OS1
  - Traffic sign with high reflectivity

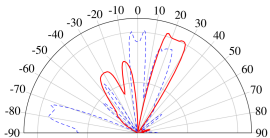
$\rightarrow$ Lidar shows a shift of the peak reflectivity by $\approx 20^\circ$



Benign



DTF-based PSA



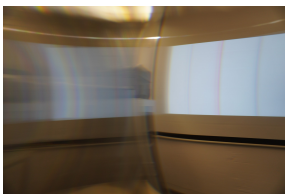
Normalized reflectivity

Physical Evaluation – Static Physical Tests

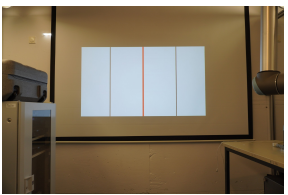
- Goal: Demonstrate physical feasibility of PSAs
- Static indoor setup in a controlled environment with DTF placed on the sensor
  - Camera: Sony α6400
  - Vertical red reference line

Physical Evaluation – Static Physical Tests

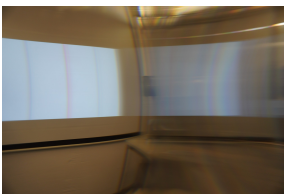
- Goal: Demonstrate physical feasibility of PSAs
- Static indoor setup in a controlled environment with DTF placed on the sensor
  - Camera: Sony α6400
  - Vertical red reference line



FoV left shift



Benign FoV

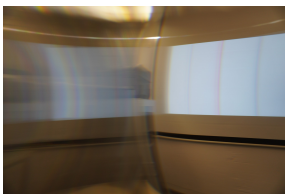


FoV right shift

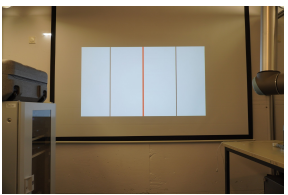
Physical Evaluation – Static Physical Tests

- Goal: Demonstrate physical feasibility of PSAs
- Static indoor setup in a controlled environment with DTF placed on the sensor
  - Camera: Sony α6400
  - Vertical red reference line

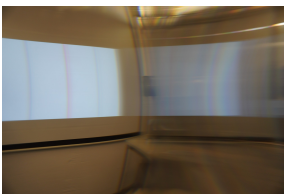
$\rightarrow$ Visible artifacts but line is visible and shifted by $\approx 20^\circ$



FoV left shift



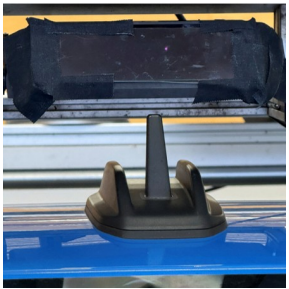
Benign FoV



FoV right shift

Physical Evaluation – Real World Tests

Goal: Evaluate PSAs in dynamic real-world environment
How can optical film-based PSAs be deployed? $\rightarrow$ Attach the film on the sensor



Attached on a real LiDAR



Attached on a front-facing camera

Physical Evaluation – LiDAR Real World Tests

- Falcon Gen2 LiDAR with 120° horizontal FoV in an autonomous driving research vehicle

Physical Evaluation – LiDAR Real World Tests

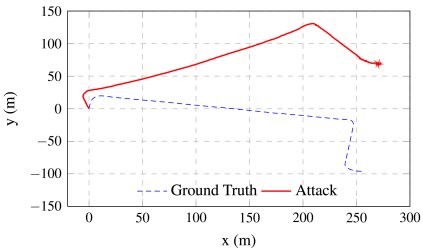
- Falcon Gen2 LiDAR with 120° horizontal FoV in an autonomous driving research vehicle
- Attack impact: Compare trajectory estimation from KISS-ICP with GNSS ground truth

Physical Evaluation – LiDAR Real World Tests

- Falcon Gen2 LiDAR with 120° horizontal FoV in an autonomous driving research vehicle
- Attack impact: Compare trajectory estimation from KISS-ICP with GNSS ground truth
- Minor adversarial perception impact: Detection confidence (Pointpillars and SECOND)

Physical Evaluation – LiDAR Real World Tests

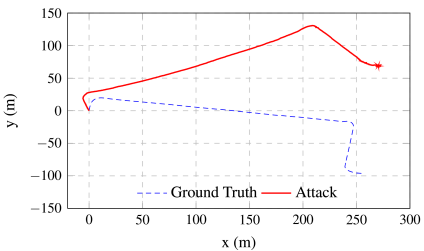
- Falcon Gen2 LiDAR with 120° horizontal FoV in an autonomous driving research vehicle
- Attack impact: Compare trajectory estimation from KISS-ICP with GNSS ground truth
- Minor adversarial perception impact: Detection confidence (Pointpillars and SECOND)



Impact on KISS-ICP

Physical Evaluation – LiDAR Real World Tests

- Falcon Gen2 LiDAR with 120° horizontal FoV in an autonomous driving research vehicle
- Attack impact: Compare trajectory estimation from KISS-ICP with GNSS ground truth
- Minor adversarial perception impact: Detection confidence (Pointpillars and SECOND)



Impact on KISS-ICP

Object detection confidence

Object	Pointpillars		SECOND	
	Benign	PSA	Benign	PSA
Car	68.39%	68.90%	70.60%	72.34%
Pedestrian	68.40%	60.50%	67.12%	63.93%
Bike	69.39%	– %*	68.20%	63.92%

*Bikes often outside FoV

Physical Evaluation – Camera Real World Tests

- Sony IMX500 with 66° horizontal FoV in a vehicle

Physical Evaluation – Camera Real World Tests

- Sony IMX500 with 66° horizontal FoV in a vehicle
- Attack impact: Compare lane detection with HybridNets

Physical Evaluation – Camera Real World Tests

- Sony IMX500 with 66° horizontal FoV in a vehicle
- Attack impact: Compare lane detection with HybridNets
- Minor adversarial perception impact: Detection confidence (Faster R-CNN and YOLOv10)

Physical Evaluation – Camera Real World Tests

- Sony IMX500 with 66° horizontal FoV in a vehicle
- Attack impact: Compare lane detection with HybridNets
- Minor adversarial perception impact: Detection confidence (Faster R-CNN and YOLOv10)



Impact on HybridNets

Physical Evaluation – Camera Real World Tests

- Sony IMX500 with 66° horizontal FoV in a vehicle
- Attack impact: Compare lane detection with HybridNets
- Minor adversarial perception impact: Detection confidence (Faster R-CNN and YOLOv10)

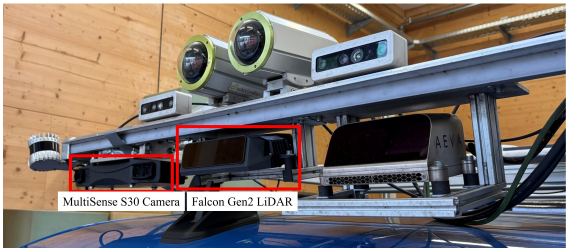


Impact on HybridNets

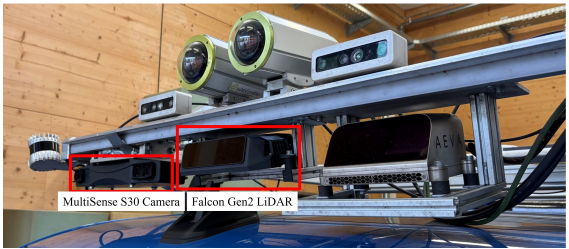
Object detection confidence

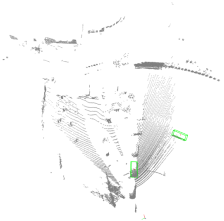
Object	Faster R-CNN		YOLOv10	
	Benign	PSA	Benign	PSA
Car	95.33%	95.10%	79.69%	78.30%
Bicycle	92.24%	94.50%	69.21%	83.49%
Person	93.66%	91.47%	78.34%	72.57%
Motorcycle	96.26%	85.81%	75.33%	69.78%
Bus	88.59%	91.81%	75.25%	68.74%
Truck	92.19%	88.40%	74.54%	74.41%
Traffic Light	94.69%	88.69%	69.63%	65.41%

Physical Evaluation – Multimodal Real World Tests



Physical Evaluation – Multimodal Real World Tests







Physical Evaluation – Observations

- DTF-based PSAs can be physically deployed on real vehicles

Physical Evaluation – Observations

- DTF-based PSAs can be physically deployed on real vehicles
- LiDAR and camera data is affected

Physical Evaluation – Observations

- DTF-based PSAs can be physically deployed on real vehicles
- LiDAR and camera data is affected
- Only minor impact on detector performance despite visual artifacts

Physical Evaluation – Observations

- DTF-based PSAs can be physically deployed on real vehicles
- LiDAR and camera data is affected
- Only minor impact on detector performance despite visual artifacts
- Multimodal attacks are possible by coherently applying PSAs

Attack Detection – LiDAR

Observations from the real-world evaluation:

- Optical film introduces smoothening artifacts

Attack Detection – LiDAR

Observations from the real-world evaluation:

- Optical film introduces smoothening artifacts
- Quantify the effect via fourier transform on the reflectivity signal
  $\rightarrow$ Smoothening removes high-frequency components

Attack Detection – LiDAR

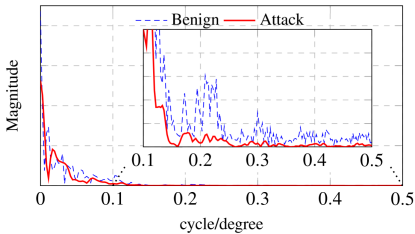
Observations from the real-world evaluation:

- Optical film introduces smoothening artifacts
- Quantify the effect via fourier transform on the reflectivity signal
  $\rightarrow$ Smoothening removes high-frequency components
- Calculate High-Frequency Energy Ratio: $\mathrm{HFR} = \frac{|\mathcal{R}_{\mathrm{cutoff}}|^2}{|\mathcal{R}_{\mathrm{total}}|^2}$

Attack Detection – LiDAR

Observations from the real-world evaluation:

- Optical film introduces smoothening artifacts
- Quantify the effect via fourier transform on the reflectivity signal
  $\rightarrow$ Smoothening removes high-frequency components
- Calculate High-Frequency Energy Ratio: $\mathrm{HFR} = \frac{|\mathcal{R}_{\mathrm{cutoff}}|^2}{|\mathcal{R}_{\mathrm{total}}|^2}$



Attack Detection – Camera

Observations from the real-world evaluation:

- Relative fix-points are included in the image $\rightarrow$ Example: Engine hood

Attack Detection – Camera

Observations from the real-world evaluation:

- Relative fix-points are included in the image $\rightarrow$ Example: Engine hood
- Perform semantic segmentation and approximate shape of these fixed parts

Attack Detection – Camera

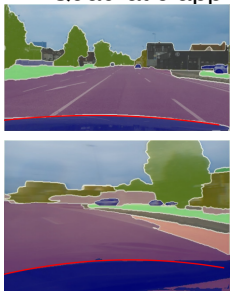
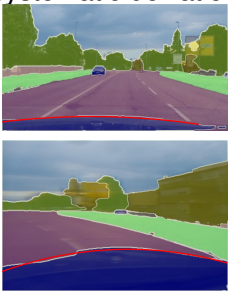
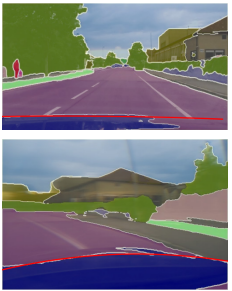
Observations from the real-world evaluation:

- Relative fix-points are included in the image $\rightarrow$ Example: Engine hood
- Perform semantic segmentation and approximate shape of these fixed parts
- Quadratic approximation shows systematic deviations

Attack Detection – Camera

Observations from the real-world evaluation:

- Relative fix-points are included in the image $\rightarrow$ Example: Engine hood
- Perform semantic segmentation and approximate shape of these fixed parts
- Quadratic approximation shows systematic deviations

Conclusion

- Perspective Shift Attacks as a new attack vector
  - Change of perceived FoV instead of environment
  - Multimodal against LiDAR and camera

Conclusion

- Perspective Shift Attacks as a new attack vector
  - Change of perceived FoV instead of environment
  - Multimodal against LiDAR and camera
- Comprehensive Evaluation
  - Digital simulation
  - Real-world tests in lab and car
  - Optical-film-based attack is practical

Conclusion

- Perspective Shift Attacks as a new attack vector
  - Change of perceived FoV instead of environment
  - Multimodal against LiDAR and camera
- Comprehensive Evaluation
  - Digital simulation
  - Real-world tests in lab and car
  - Optical-film-based attack is practical
- Attack Detection
  - Detailed analysis on already captured data
  - Can be deployed without additional hardware effort

Conclusion

- Perspective Shift Attacks as a new attack vector
  - Change of perceived FoV instead of environment
  - Multimodal against LiDAR and camera
- Comprehensive Evaluation
  - Digital simulation
  - Real-world tests in lab and car
  - Optical-film-based attack is practical
- Attack Detection
  - Detailed analysis on already captured data
  - Can be deployed without additional hardware effort

Thank you