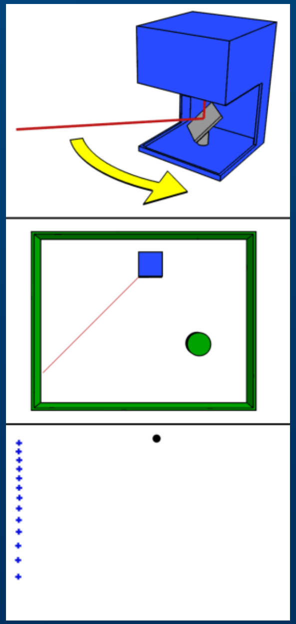
Performance Analysis of a LiDAR System for Comprehensive Airport Ground Surveillance under Varying Weather and Lighting Conditions



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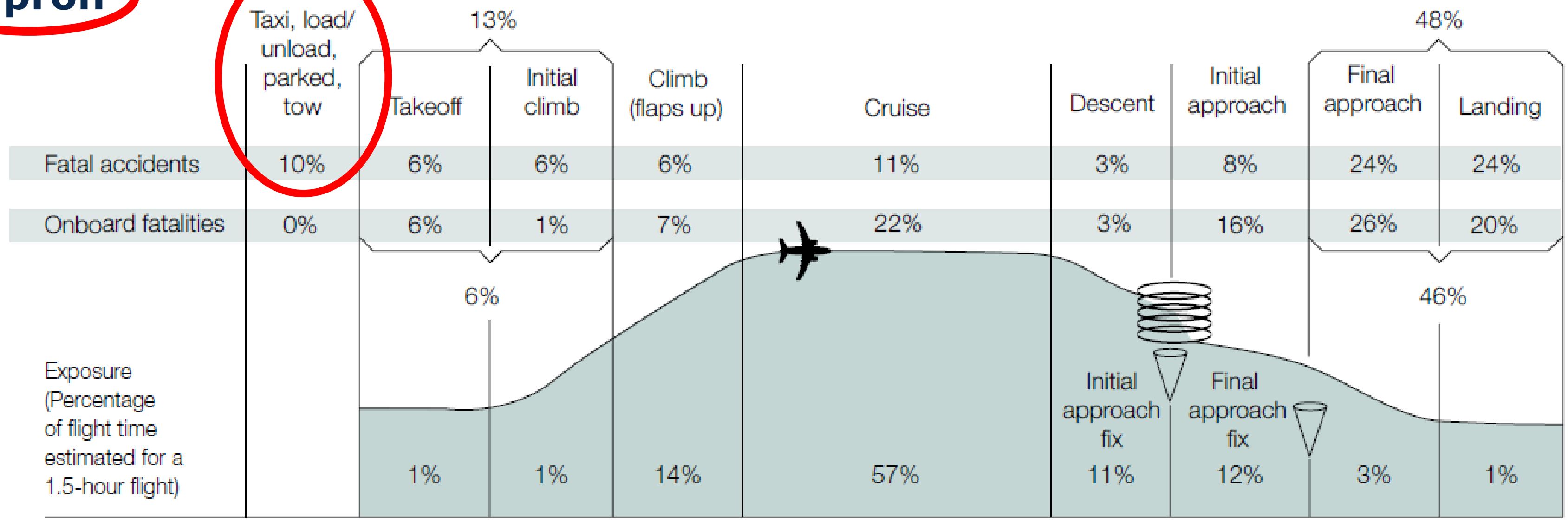
The need for risk mitigation on the apron

- All current ATM concepts / ConOps call for significantly improved safety targets (e.g. SESAR, ICAO GANP, NextGen) **"x10"**
- the contribution of **airport surface operations** to Aviation risk is substantial (injuries to human health and damage to material)
- areas affected by surface operations:
  - manoeuvring area
  - **apron**

Percentage of fatal accidents and onboard fatalities



Note: Percentages may not sum to 100% due to numerical rounding.

Source: Boeing Statsum 2017

Enhancing airport ground surveillance using LiDAR data

We need a precise and continuous representation of the traffic situtation on the apron

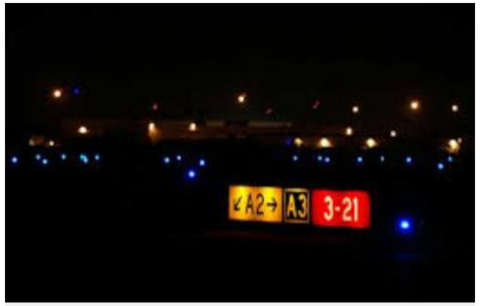
Potential risks/capacity backlogs due to:

Sensiive Line-of-sight dependencies of the OTWV,

Lack of precision/accuracy of conventional airport sensors (CCTV),

Challenging weather and lighting conditions → LVOs: CAT III A, B, C,

Degraded situational awareness of the ATCO during these times



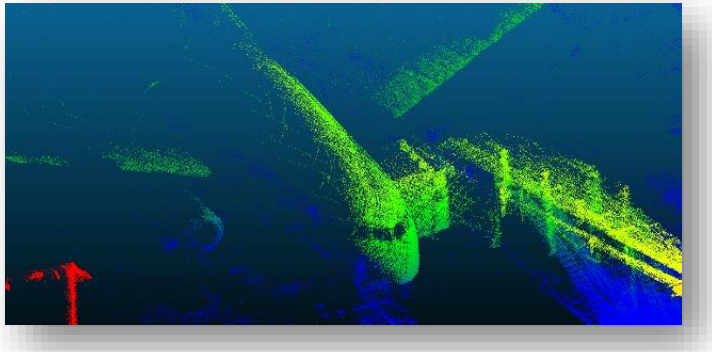
Visual range < 50m

Visual range < 200m

LiDAR sensing contributes to a precise and continuous representation of the traffic situation

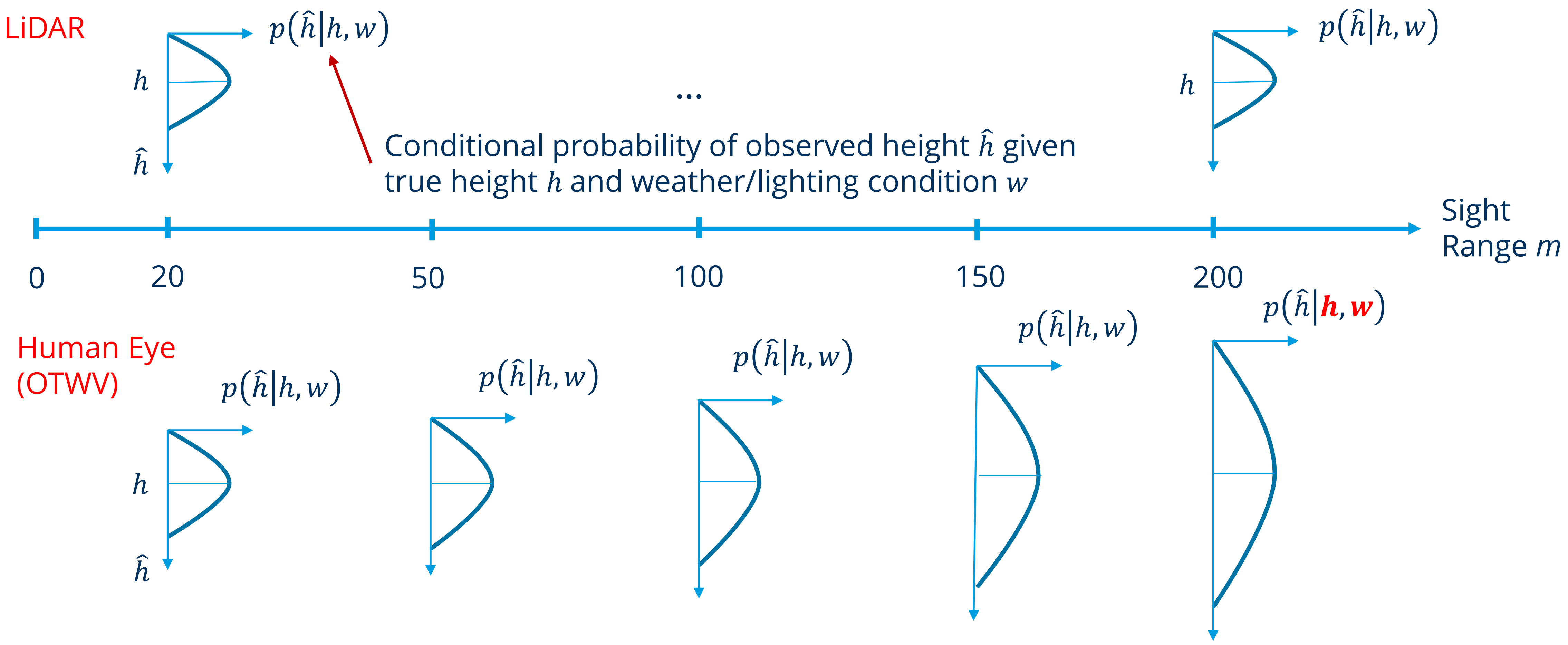
non-cooperative, wide angles of detection, precision and accuracy
at millimeter range level (λ vary to suit the target:
from about 10 micrometers to the UV (approximately 250 nm)),
no multipath effects, less sensitive to weather and lighting conditions
(but more sensitive to weather than e.g., SMR : λ ca. 0,3 m)

Ø → Raindrop: 0,5 – 1 mm, Fog: 0,001 – 0,005 mm



Enhancing airport ground surveillance using LiDAR data

Vertical accuracy of LiDAR vs. human eye with increasing viewing distance



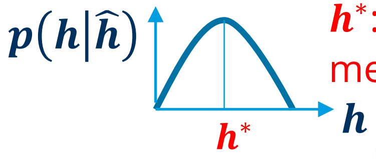
Conditional probability of observed height $\hat{h}$ given true height h and weather/lighting condition w

LiDAR-based airport ground surveillance under varying weather and lighting conditions

Contribution and vision (1)

Validated vertical accuracy of LiDAR measurements for two weather scenarios and two lighting scenarios

Developed probabilistic sensor model that integrates wheather and lighting → foundation for automatic controller assistance functions to foster situational awareness of ATCO



h^*: most likely height h given measured height $\hat{h}$

(Meyer, Fricke et al., 2013, Mund, Fricke et al., 2014)

(Mund, Fricke et al. 2015, 2016, current)

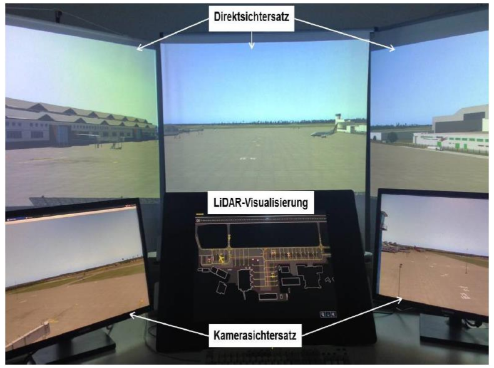
LiDAR sensor at DRS

→ Object detection, e.g. height over ground → Weather/lighting-aware probabilistic sensor model →

3-D point cloud

Height estimates $\hat{h}$

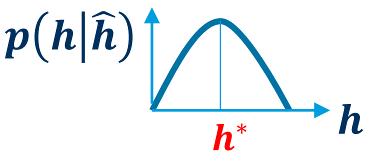
Ground truth (GT) heights h



Synthetic ground position GUI enhanced with **automatic controller assistance functions derived from sensor model**

LiDAR-based airport ground surveillance under varying weather and lighting conditions

Contribution and vision (2)



$\boldsymbol{h}^*$: most likely height $\boldsymbol{h}$ given measured height $\hat{\boldsymbol{h}}$

$$\boldsymbol{h}^* = \arg\max_{h} p(h|\hat{h})$$

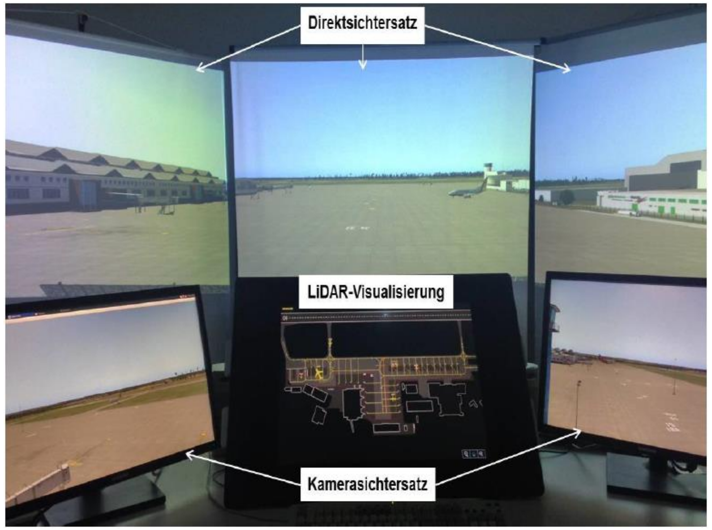
Motivating example

Object on the apron → true height h = 0,5m

CAVOK conditions given:
Sensor model: h^*= 0,51m → $p(h^*|\hat{h})$ = 0.99 → ok ☺

CAT III A/B conditions given:
Sensor model: h^* = 0,002 m → $p(h^*|\hat{h})$ = 0.99 → Low accuracy ☹

Goal: Achieve a high quality and weather robust performance):
Sensor model: h^*= 0,53 m → $p(h^*|\hat{h})$ = 0.99 → ok ☺



We want to build a sensor model that works as accurate as possible under any given weather condition!

LiDAR-based airport ground surveillance under varying weather and lighting conditions

Experimental Setup: Detecting objects on the apron using the height over ground attribute

Height over ground measure indicates presence of objects on the apron: simple and fast to compute, pose (translation, rotation) invariant, reasonably robust to partial occlusions

Varying weather and lighting conditions give rise to different degrees of noise, outliers, non-uniform sampling, misalignments in height measurements

Data acquisition

Data	Scenario A	Scenario B	Sensor distance
Set 1 (6 objects, 10 – 100 cm)	Daylight, Rain	Daylight, Clear	25m, 60m, 95m, 130m
Set 2 (10 objects, 10 – 100 cm)	Daylight, Clear	Night, Clear	25m, 60m, 95m, 130m

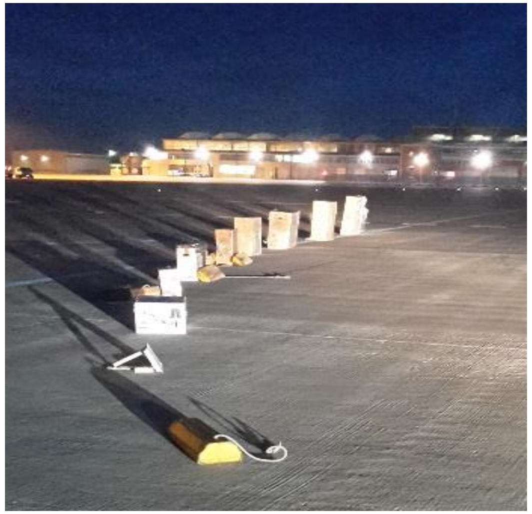


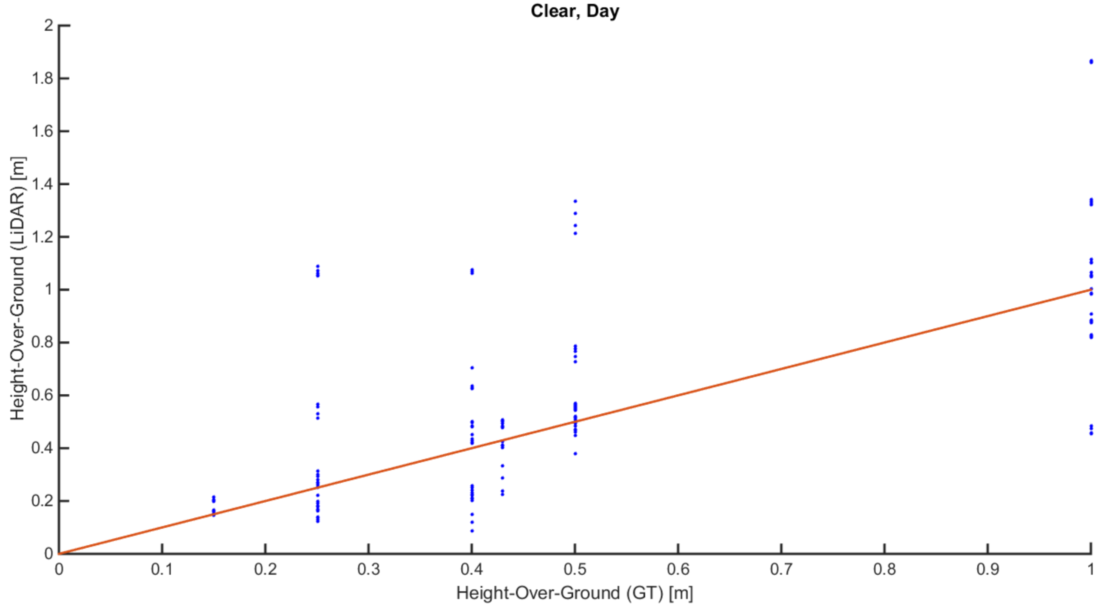
Figure: Data set 2, Scenario B (Night, Clear), Sensor distance: 25 m

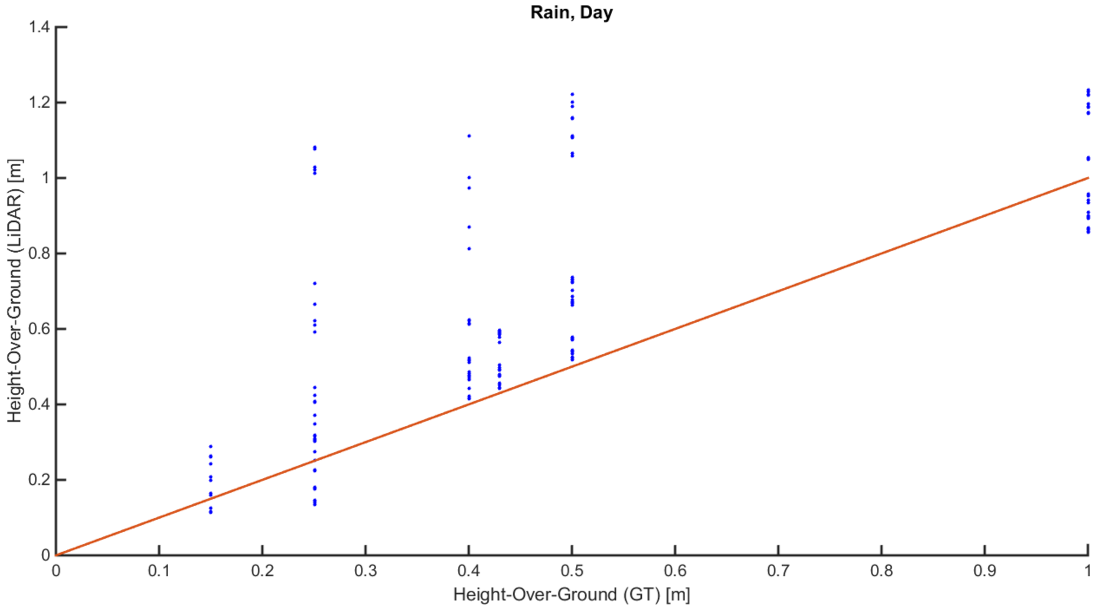
LiDAR-based airport ground surveillance under varying weather and lighting conditions

Measured object height as a function of the true object height: **Data set 1**

Left: Scenario A → **w = {Clear, Day}** , Right: Scenario B → **w = {Rain, Day}**

Each scenario w gives rise to a conditional distribution $p(h,\hat{h}|w)$ referred to as **height over ground distribution**.



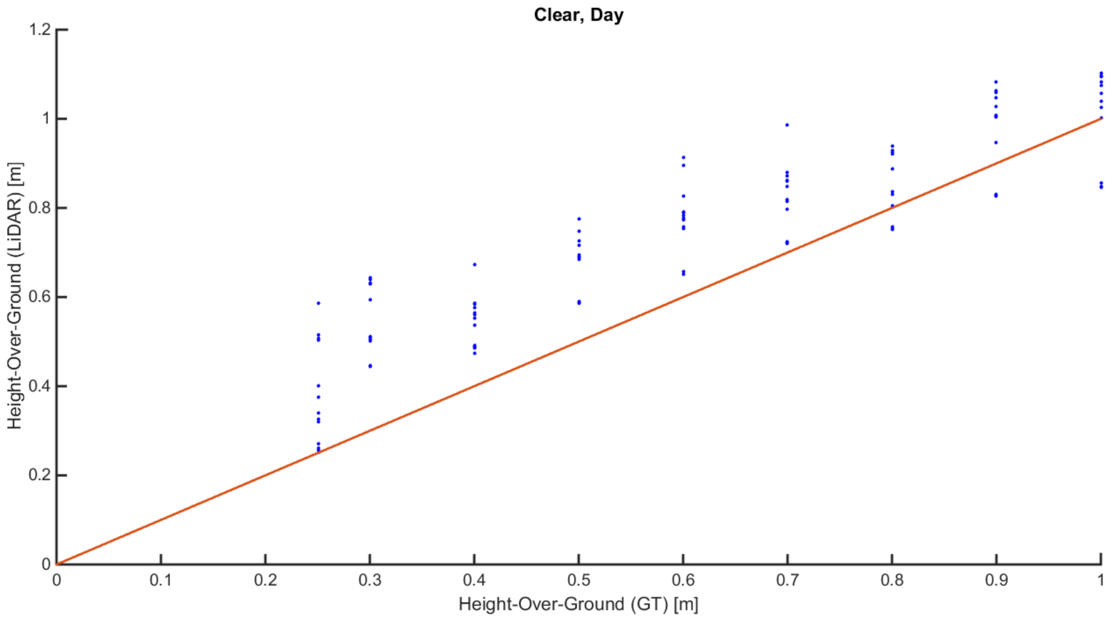


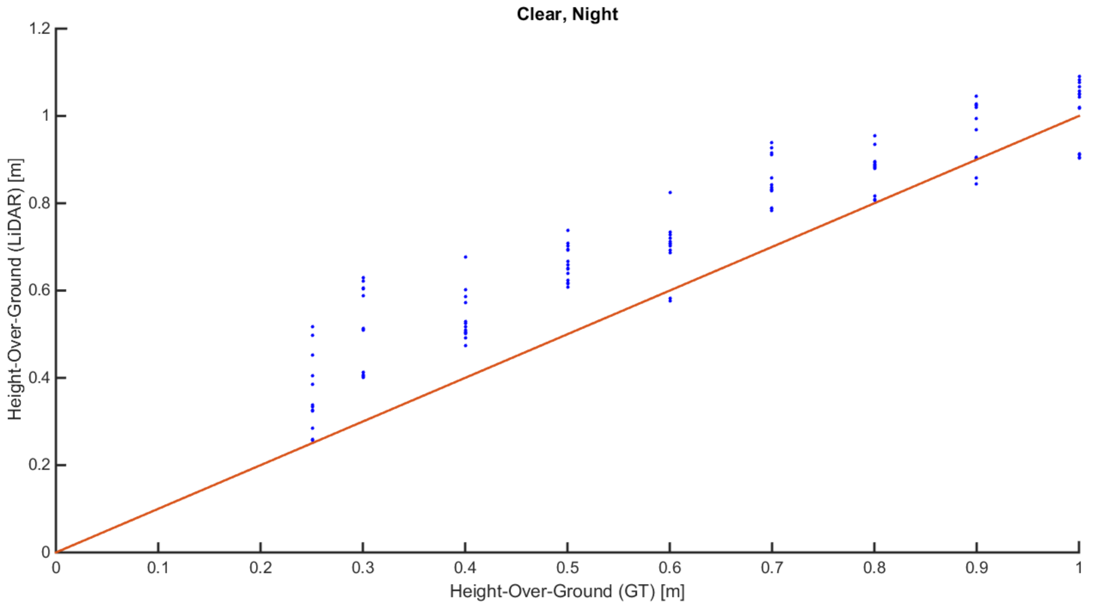
LiDAR-based airport ground surveillance under varying weather and lighting conditions

Measured object height as a function of the true object height: **Data set 2**

Left: Scenario A → ***w* = {Clear, Day}** , Right: Scenario B → ***w* = {Clear, Night}**

Each scenario w gives rise to a conditional distribution $p(h, \hat{h}|w)$ referred to as **height over ground distribution**.


Clear, Day


Clear, Night

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Using the height over ground distributions to determine the sensor accuracy (1)

For each height over ground distribution $p(h, \hat{h}|w)$ we quantify the sensor accuracy in terms of the error function:

$$Err = \frac{1}{N}\sum_{n=1}^{N}\left|h_n - \hat{h}_n\right|,$$ N: number of 3-D points

True height associated with point n

Measured height associated with point n

The function Err is also referred to as **recognition error**.

Absolute values used to be more robust against measurement outliers!

LiDAR-based airport ground surveillance under varying weather and lighting conditions

Using the height over ground distributions to determine the sensor accuracy (2)

$Err = \frac{1}{N}\sum_{n=1}^{N}\left|h_n - \hat{h}_n\right|, N$: number of 3-D points

Two weather scenarios

Data Set 1	Clear	Rain
Daylight	Err = 0.11 m	Err = 0.18 m

Two lighting scenarios

Data Set 2	Daylight	Night
Clear	Err = 0.16 m	Err = 0.14 m

LiDAR tends to be more robust to varying lighting conditions (right table) in contrast to the investigated variation of weather scenarios (left table).

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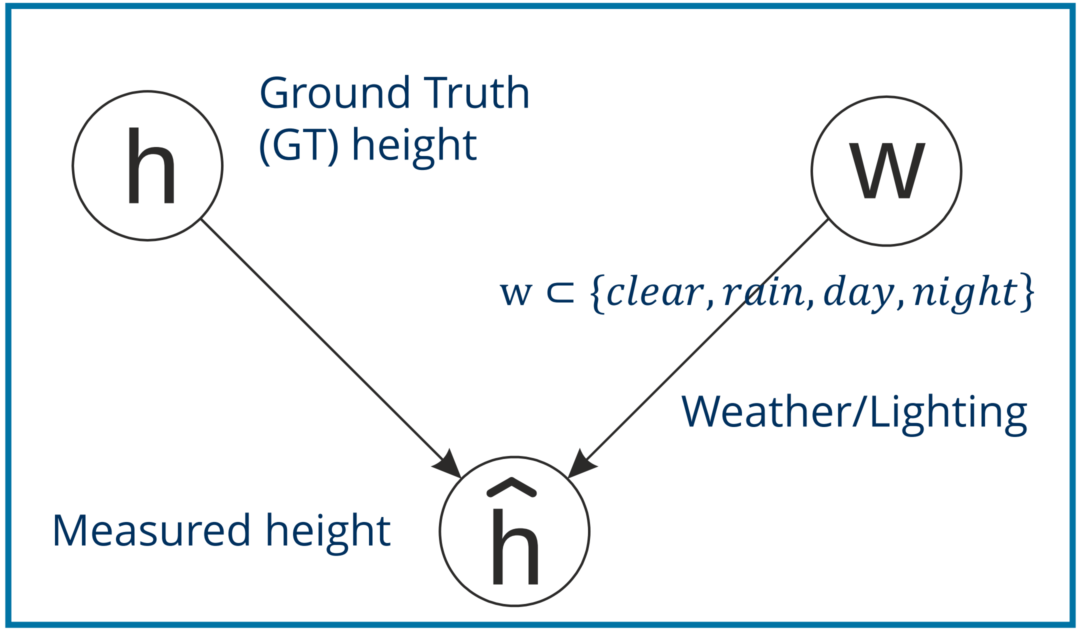
Building a weather/lighting-aware probabilistic sensor model (1)



h

Ground Truth (GT) height

w

$w \subset \{clear, rain, day, night\}$

Weather/Lighting

Measured height

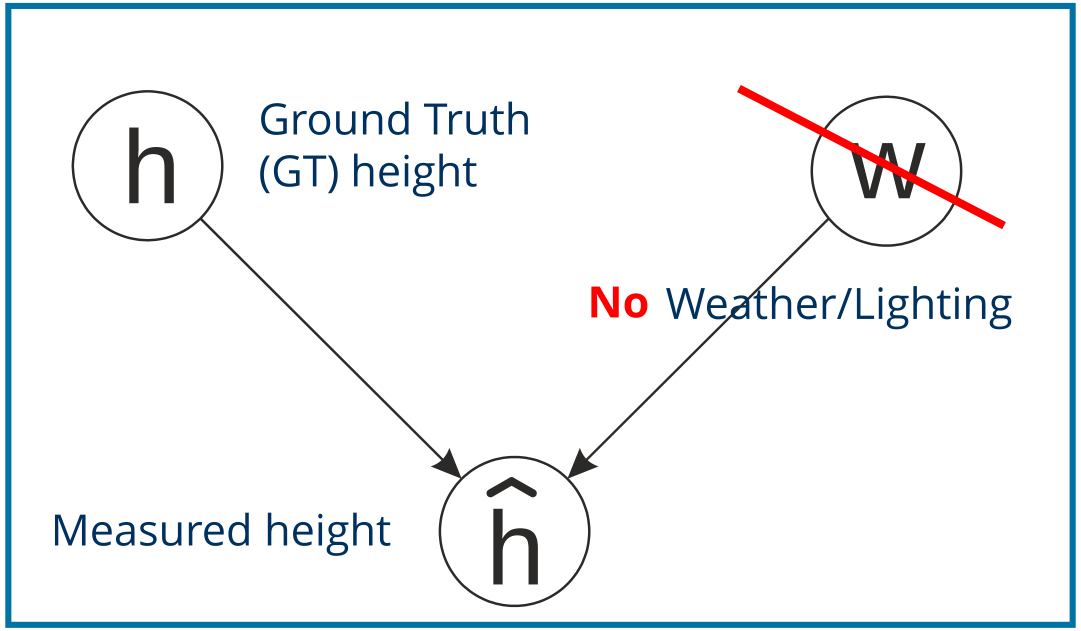
$\hat{h}$

Probabilistic graphical model captures the sensor behavior in terms of directed dependencies between the variables h, w, $\hat{h}$ of the underlying joint probability distribution $p(h, w, \hat{h})$.

We are interested in the conditional distribution $p(h|\hat{h})$ over true object heights h given measured height $\hat{h}$.

LiDAR-based airport ground surveillance under varying weather and lighting conditions

Building a weather/lighting-aware probabilistic sensor model (2)



Ground Truth (GT) height

No Weather/Lighting

Measured height

No Weather/Lighting:

$$p(h,\hat{h}) = p(h|\hat{h})p(\hat{h})$$

Learn joint probability using an Expectation Maximization (EM) algorithm

$$p(h|\hat{h}) \approx \frac{p(h,\hat{h})}{\sum_{h'} p(h',\hat{h})}$$

compute conditional distribution over the approximated sum of the true heights h‘
„Baseline“

We are interested in the conditional distribution $p(h|\hat{h})$ over true object heights h given measured height $\hat{h}$.

Short Excurse: Probabilistic Sensor Model

Deriving the conditional probability $p(h|\hat{h})$

Discrete prior on w

Conditional probability query

$$p(h|\hat{h}) = \frac{p(h,\hat{h})}{p(\hat{h})} = \frac{p(h,\hat{h})}{\int p(h',\hat{h})dh'} \approx \frac{p(h,\hat{h})}{\sum_{h'} p(h',\hat{h})} = \frac{\sum_w p(h,\hat{h},w)}{\sum_w \sum_{h'} p(h',\hat{h})} = \frac{\sum_w p(h,\hat{h}|w)p(w)}{\sum_w \sum_{h'} p(h,\hat{h}|w)p(w)}$$

Marginalize over true height: h'

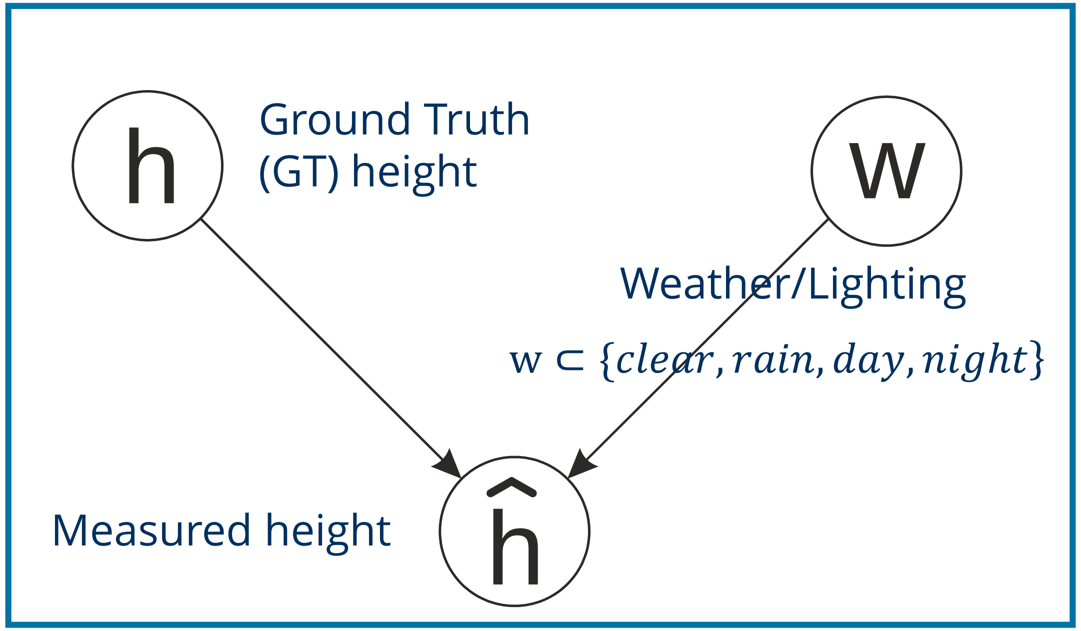
$\int \ldots \rightarrow \sum \ldots$

Marginalize over (hidden) variable w

Conditioning on w

LiDAR-based airport ground surveillance under varying weather and lighting conditions

Building a weather/lighting-aware probabilistic sensor model (3)



h

Ground Truth (GT) height

w

Weather/Lighting

$\mathrm{w} \subset \{clear, rain, day, night\}$

Measured height

$\hat{h}$

Weather/Lighting-aware:

$$p(h|\hat{h}) \approx \frac{\sum_w \boxed{p(h,\hat{h}|w)}\boxed{p(w)}}{\sum_w \sum_{h'} \boxed{p(h',\hat{h}|w)}\boxed{p(w)}}$$

Height over ground distribution

No assumptions on weather/lighting: $p(w)$ unformly distributed over all sceanrios w

Weather-aware (two scenarios)

w = {day, clear}, w = {day, rain} ⟶ $p(w)$ = 0,5

Lighting-aware (two scenarios)

w = {day, clear}, w = {night, clear} ⟶ $p(w)$ = 0,5

We are interested in the conditional distribution $p(h|\hat{h})$ over true object heights h given measured height $\hat{h}$.

LiDAR-based airport ground surveillance under varying weather and lighting conditions

Performance analysis of the probabilistic sensor model

Compare recognition error of **weather/lighting-aware** model against **baseline** model over test data

1) Infer most likely height $h^* = \arg\max_h p(h|\hat{h})$ over test data
2) Compute recognition error Err for both models over test data via $Err = \frac{1}{N}\sum_{n=1}^{N}|h_n^* - \hat{h}_n|$,

Recognition error Err	Baseline	Weather/Lighting-aware
Data Set 1: Day, Clear/Day Rain	$Err = 0.13$ m	$Err = 0.082$ m
Data Set 2: Clear, Day/Clear, Night	$Err = 0.073$ m	$Err = 0.069$ m

a) Weather-aware model achieves a performance improvement of 37% over test data compared to baseline
b) Lighting-aware model peforms similar to baseline over test data
c) Sensor uncertainty less effected by varying lighting conditions vs. varying weather conditions

LiDAR-based airport ground surveillance under varying weather and lighting conditions

Conclusions and future work

1) Specific, parametrized height over ground distribution of objects on the apron under different weather/lighting conditions
2) Developed weather/lighting-aware probabilistic sensor model: **sensor model tends to be more robust the simple baseline model**
3) Derive automatic controller assistance functions from weather/lighting-aware probabilistic sensor model to foster situational awareness of ATCO (e.g., object detected on the apron with 0,1% or 99% probability)
4) Investigate sensor performance under presence of fog: major cause for LVOs
5) Extend / differentiate further operational weather categories („CAT IV"),
6) Validate range dependencies of height measurements (supposed none so far).