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

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### Percentage of fatal accidents and onboard fatalities

<table>
<thead>
<tr>
<th>Stage</th>
<th>Fatal accidents</th>
<th>Onboard fatalities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taxi, load/ unload, parked, tow</td>
<td>10%</td>
<td>0%</td>
</tr>
<tr>
<td>Takeoff</td>
<td>6%</td>
<td>6%</td>
</tr>
<tr>
<td>Initial climb</td>
<td>6%</td>
<td>1%</td>
</tr>
<tr>
<td>Climb (flaps up)</td>
<td>6%</td>
<td>7%</td>
</tr>
<tr>
<td>Cruise</td>
<td>11%</td>
<td>22%</td>
</tr>
<tr>
<td>Descent</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>Initial approach</td>
<td>8%</td>
<td>16%</td>
</tr>
<tr>
<td>Final approach</td>
<td>24%</td>
<td>26%</td>
</tr>
<tr>
<td>Landing</td>
<td>24%</td>
<td>20%</td>
</tr>
</tbody>
</table>

Exposure (Percentage of flight time estimated for a 1.5-hour flight):

- Initial approach fix: 11%
- Final approach fix: 12%
- Initial approach: 1%
- Final approach: 3%
- Landing: 1%

Source: Boeing Statsum 2017
Enhancing airport ground surveillance using LiDAR data

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

Potential risks/capacity backlogs due to:

- Sensitive 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

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

LiDAR

\[ p(\hat{h}|h, w) \]

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

Human Eye (OTWV)

\[ p(\hat{h}|h, w) \]

Sight Range \( m \)
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 weather and lighting → foundation for automatic controller assistance functions to foster situational awareness of ATCO

(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

Height estimates $\hat{h}$

Ground truth (GT) heights $h$

$p(h|\hat{h})$: most likely height $h$ given measured height $\hat{h}$

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

(Meyer, Fricke et al., 2013, Mund, Fricke et al., 2014) (Mund, Fricke et al. 2015, 2016, current)
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Contribution and vision (2)

Motivating example

Object on the apron $\rightarrow$ true height $h = 0.5m$

CAVOK conditions given:
Sensor model: $h^* = 0.51m \rightarrow p(h^* | \hat{h}) = 0.99 \rightarrow ok$ ☺

CAT III A/B conditions given:
Sensor model: $h^* = 0.002 m \rightarrow p(h^* | \hat{h}) = 0.99 \rightarrow Low accuracy$ ☹

Goal: Achieve a high quality and weather robust performance):
Sensor model: $h^* = 0.53 m \rightarrow p(h^* | \hat{h}) = 0.99 \rightarrow ok$ ☺

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

<table>
<thead>
<tr>
<th>Data</th>
<th>Scenario A</th>
<th>Scenario B</th>
<th>Sensor distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Set 1 (6 objects, 10 – 100 cm)</td>
<td>Daylight, Rain</td>
<td>Daylight, Clear</td>
<td>25m, 60m, 95m, 130m</td>
</tr>
<tr>
<td>Set 2 (10 objects, 10 – 100 cm)</td>
<td>Daylight, Clear</td>
<td>Night, Clear</td>
<td>25m, 60m, 95m, 130m</td>
</tr>
</tbody>
</table>

Figure: Data set 2, Scenario B (Night, Clear), Sensor distance: 25 m
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Measured object height as a function of the true object height: **Data set 1**

Left: Scenario A $\rightarrow w = \{\text{Clear, Day}\}$, Right: Scenario B $\rightarrow w = \{\text{Rain, Day}\}$

Each scenario $w$ gives rise to a conditional distribution $p(h, \hat{h} | w)$ referred to as **height over ground distribution**.
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Measured object height as a function of the true object height: **Data set 2**

Left: Scenario A $\rightarrow w = \{\text{Clear, Day}\}$, Right: Scenario B $\rightarrow w = \{\text{Clear, Night}\}$

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

\[
Err = \frac{1}{N} \sum_{n=1}^{N} |h_n - \hat{h}_n|, \quad N: \text{number of 3-D points}
\]

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)

\[
Err = \frac{1}{N} \sum_{n=1}^{N} |h_n - \hat{h}_n|, \quad N: \text{number of 3-D points}
\]

<table>
<thead>
<tr>
<th>Data Set 1</th>
<th>Data Set 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Clear</strong></td>
<td><strong>Daylight</strong></td>
</tr>
<tr>
<td><strong>Rain</strong></td>
<td><strong>Night</strong></td>
</tr>
<tr>
<td><strong>Daylight</strong></td>
<td></td>
</tr>
<tr>
<td>Err = 0.11 m</td>
<td>Err = 0.16 m</td>
</tr>
<tr>
<td>Err = 0.18 m</td>
<td>Err = 0.14 m</td>
</tr>
</tbody>
</table>

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)

Ground Truth (GT) height

Measured height

Weather/Lighting

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 \( \hat{h} \).
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Building a weather/lighting-aware probabilistic sensor model (2)

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 Excursus: Probabilistic Sensor Model

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

Conditional probability query:

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

Marginalize over true height: $h' \rightarrow \sum_{...}$

Marginalize over (hidden) variable $w$

Conditioning on $w$
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Building a weather/lighting-aware probabilistic sensor model (3)

Weather/Lighting-aware:

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

Height over ground distribution

Weather-aware (two scenarios)
$$w = \{\text{day, clear}\}, w = \{\text{day, rain}\} \quad \rightarrow \quad p(w) = 0.5$$

Lighting-aware (two scenarios)
$$w = \{\text{day, clear}\}, w = \{\text{night, clear}\} \quad \rightarrow \quad p(w) = 0.5$$

We are interested in the conditional distribution $p(h|\hat{h})$ over true object heights $h$ given measured height $\hat{h}$. 
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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 $Err = \frac{1}{N} \sum_{n=1}^{N} |h^*_n - \hat{h}_n|$

<table>
<thead>
<tr>
<th>Recognition error $Err$</th>
<th>Baseline</th>
<th>Weather/Lighting-aware</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Set 1: Day, Clear/Day Rain</td>
<td>$Err = 0.13$ m</td>
<td>$Err = 0.082$ m</td>
</tr>
<tr>
<td>Data Set 2: Clear, Day/Clear, Night</td>
<td>$Err = 0.073$ m</td>
<td>$Err = 0.069$ m</td>
</tr>
</tbody>
</table>

a) Weather-aware model achieves a performance improvement of 37% over test data compared to baseline

b) Lighting-aware model performs similar to baseline over test data

c) Sensor uncertainty less effected by varying lighting conditions vs. varying weather conditions
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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 than 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).