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MeteoSwiss

Towards Camera Based Visibility Estimation

MET Alliance ET AUTO OBS Meeting – June 3rd, 2020

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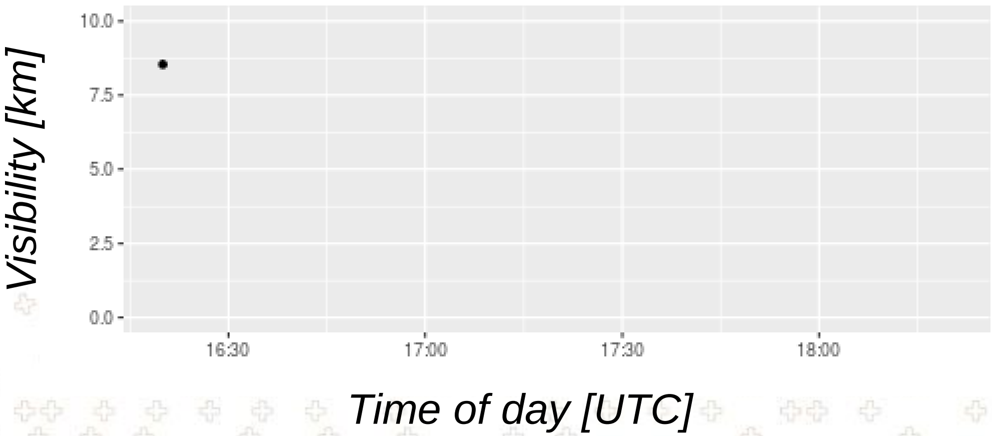
Example: Château d’Oex Camera, 17.06.2016

16:20 UTC

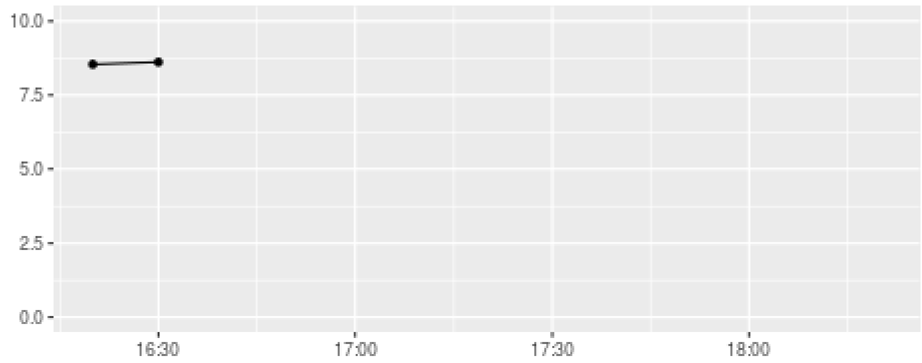
Estimated Visibility



Example: Château d’Oex Camera, 17.06.2016

16:30 UTC

Estimated Visibility



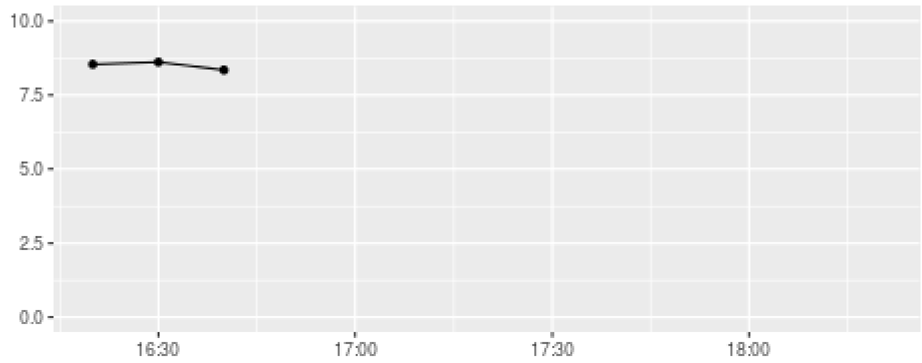
Visibility [km]

Time of day [UTC]

Example: Château d’Oex Camera, 17.06.2016

16:40 UTC

Estimated Visibility



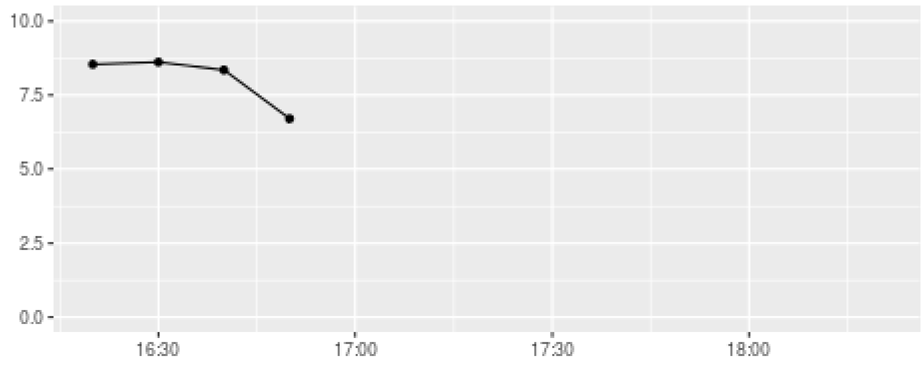
Visibility [km]

Time of day [UTC]

Example: Château d’Oex Camera, 17.06.2016

16:50 UTC

Estimated Visibility



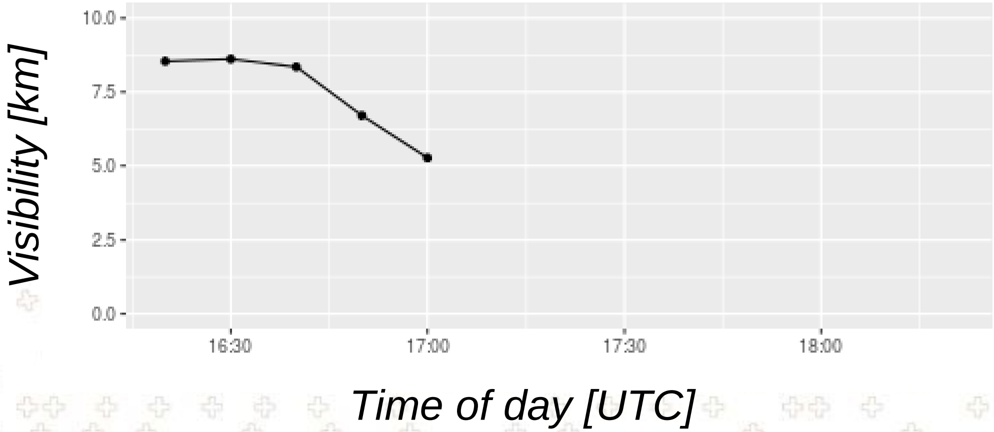
Visibility [km]

Time of day [UTC]

Example: Château d’Oex Camera, 17.06.2016

17:00 UTC

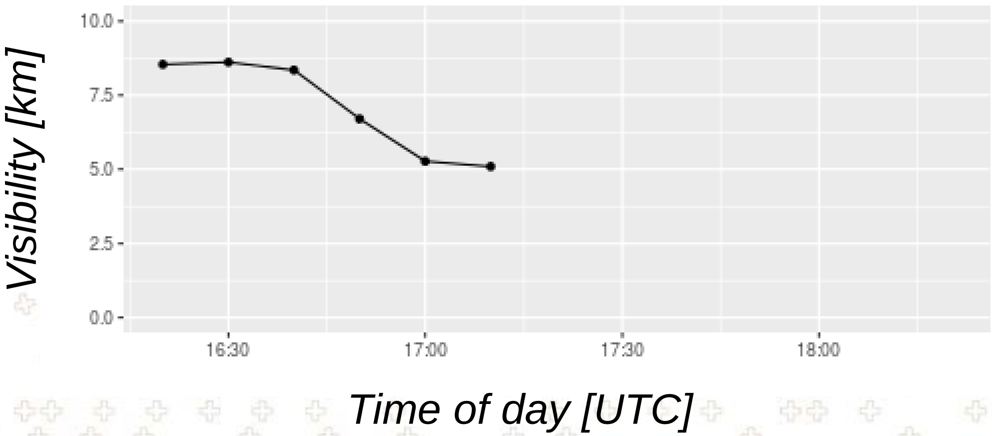
Estimated Visibility



Example: Château d’Oex Camera, 17.06.2016

17:10 UTC

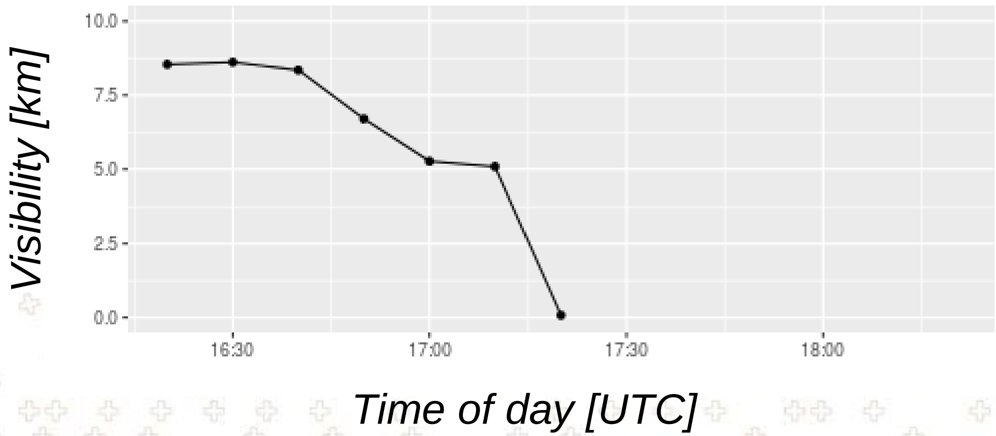
Estimated Visibility



Example: Château d’Oex Camera, 17.06.2016

17:20 UTC

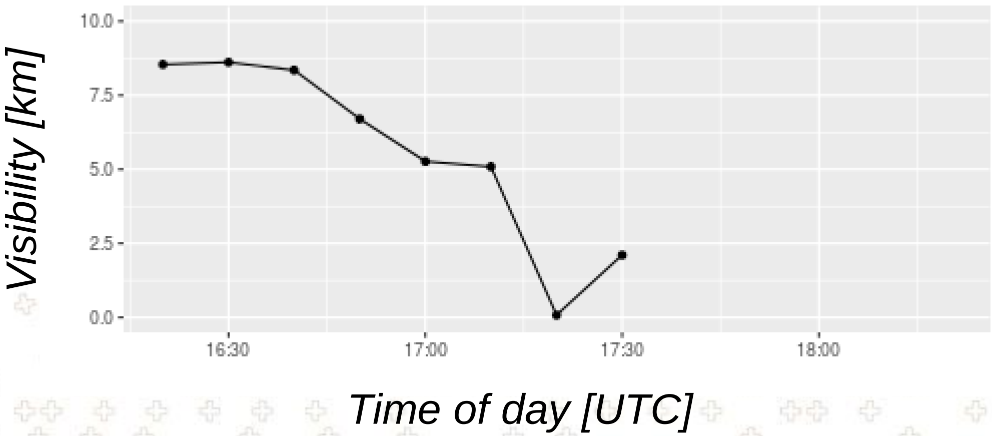
Estimated Visibility



Example: Château d’Oex Camera, 17.06.2016

17:30 UTC

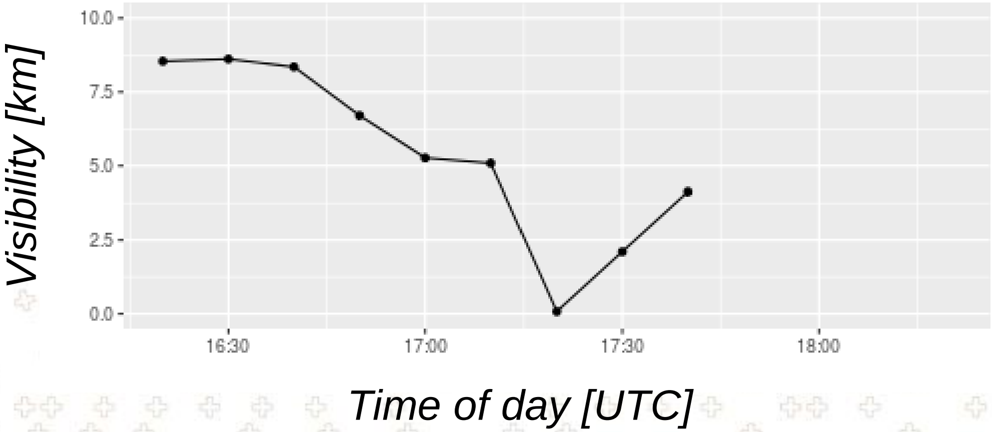
Estimated Visibility



Example: Château d’Oex Camera, 17.06.2016

17:40 UTC

Estimated Visibility



Outline

- Introduction: Motivation and Current State at MeteoSwiss
- Physical Model Approach
- Evaluation
- Improving the Camera System
- Improving the Estimation Algorithm: Learning Approach

Motivation

1. Increase spatial and temporal resolution of visibility observations
2. Generate additional benefit from existing camera network
3. Panorama cameras see more of the atmosphere than scatterometers:

→ Potential for estimates that are more representative when the atmosphere is inhomogeneous

Our Current State

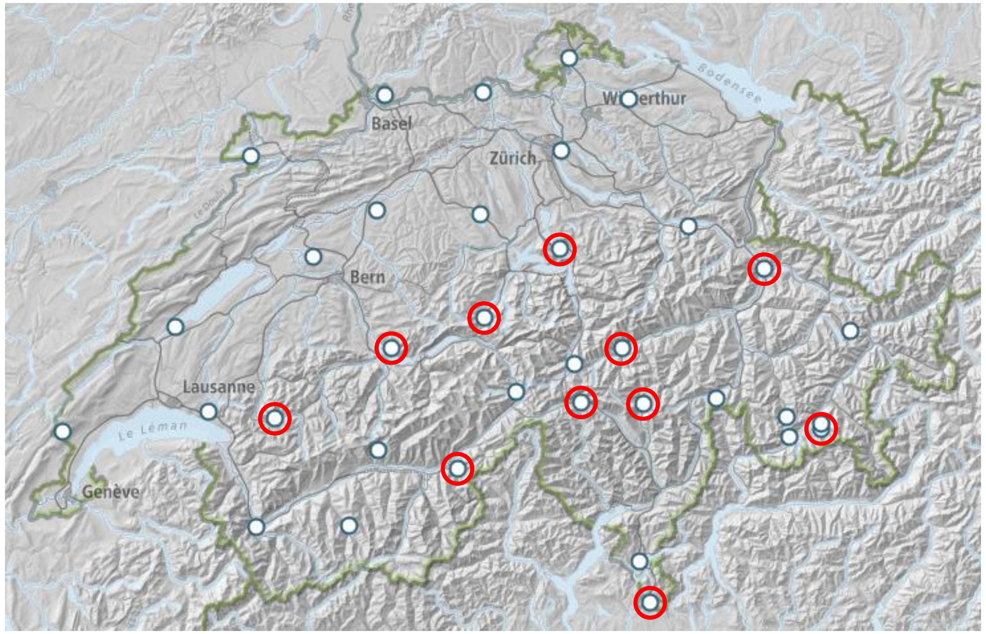
35 cameras, many along GAFOR routes

12 cameras provide estimates of the prevailing visibility every 10 min

- Operative since October 2018
- Provided on «best effort» basis only

Limited scope:

- Assist forecasters with GAFOR production
- Data is restricted to internal use



MeteoSwiss camera network (as of May 2020), visibility is estimated at stations highlighted in red

Outline

Physical Model Approach

1. Dark Channel prior: most local patches in haze-free images contain pixels with low intensities in at least one channel [He *et al.*, 2011]
2. Airlight scattered into line of sight raises minimum intensity [Koschmieder, 1924]
3. Atmospheric scattering coefficient is inversely related to visibility

$$L(d) = L_\infty(1 - e^{-\sigma d})$$

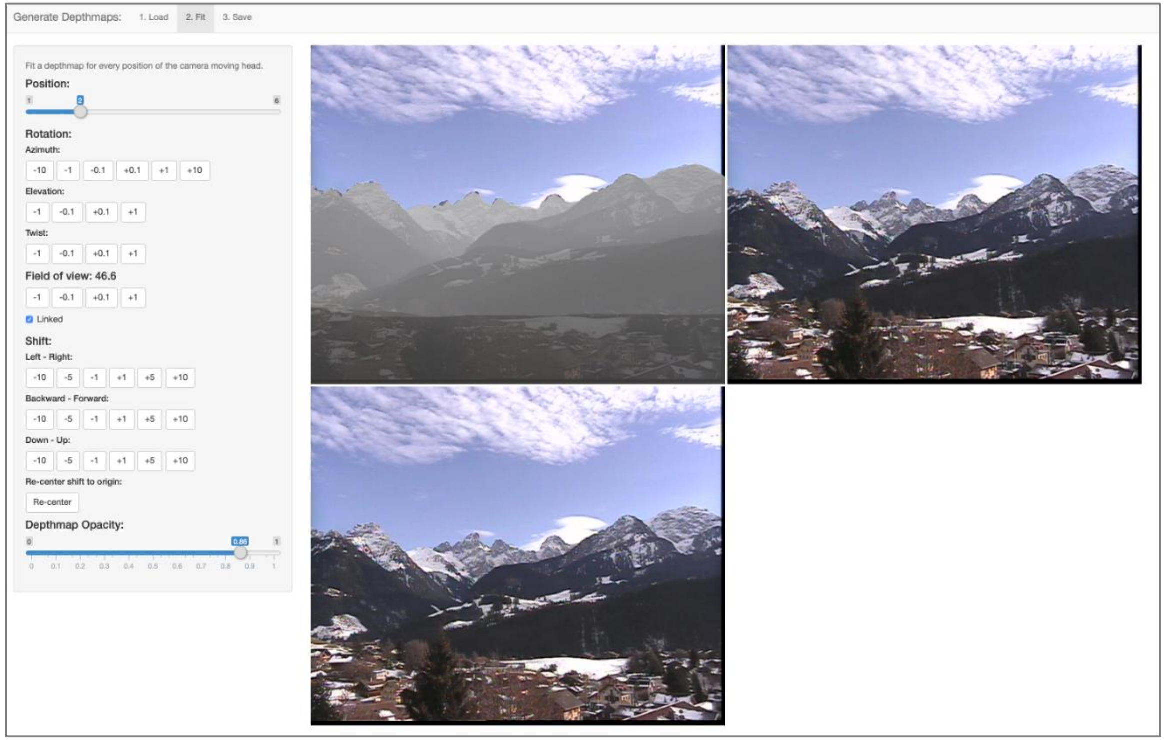
$$v \propto {}^{1}/_{\sigma}$$

Motivation:

- Avoid tuning/adaptation for every camera site
- Well understood behavior of estimation algorithm

Generating the Depth Map

- Known geolocation coordinates of cameras
- Visual matching of additional degrees of freedom

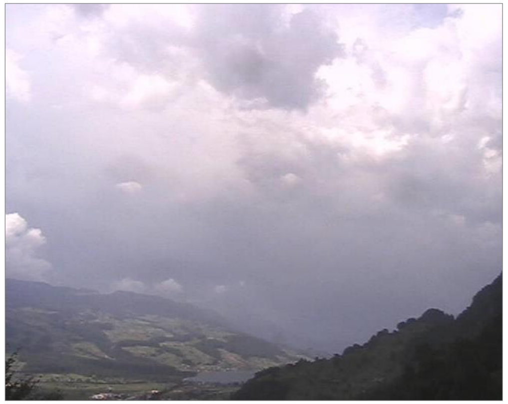


Tool for generating depth maps by visual correspondence

Alternative: Pose estimation from correspondence points [Haralick *et al.*, 1989]

Estimation Method

Input image



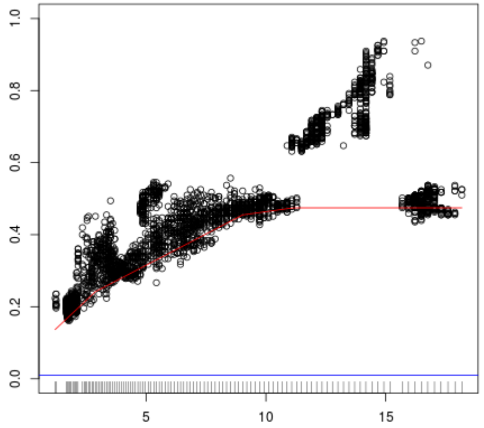
→

Dark channel

(white bands are due to edge suppression)

→

Robust quantile regression of airlight



→ $v \propto {}^{1}/_{\sigma}$

↑

Depth map

Extension of [Sutter *et al.*, 2016]

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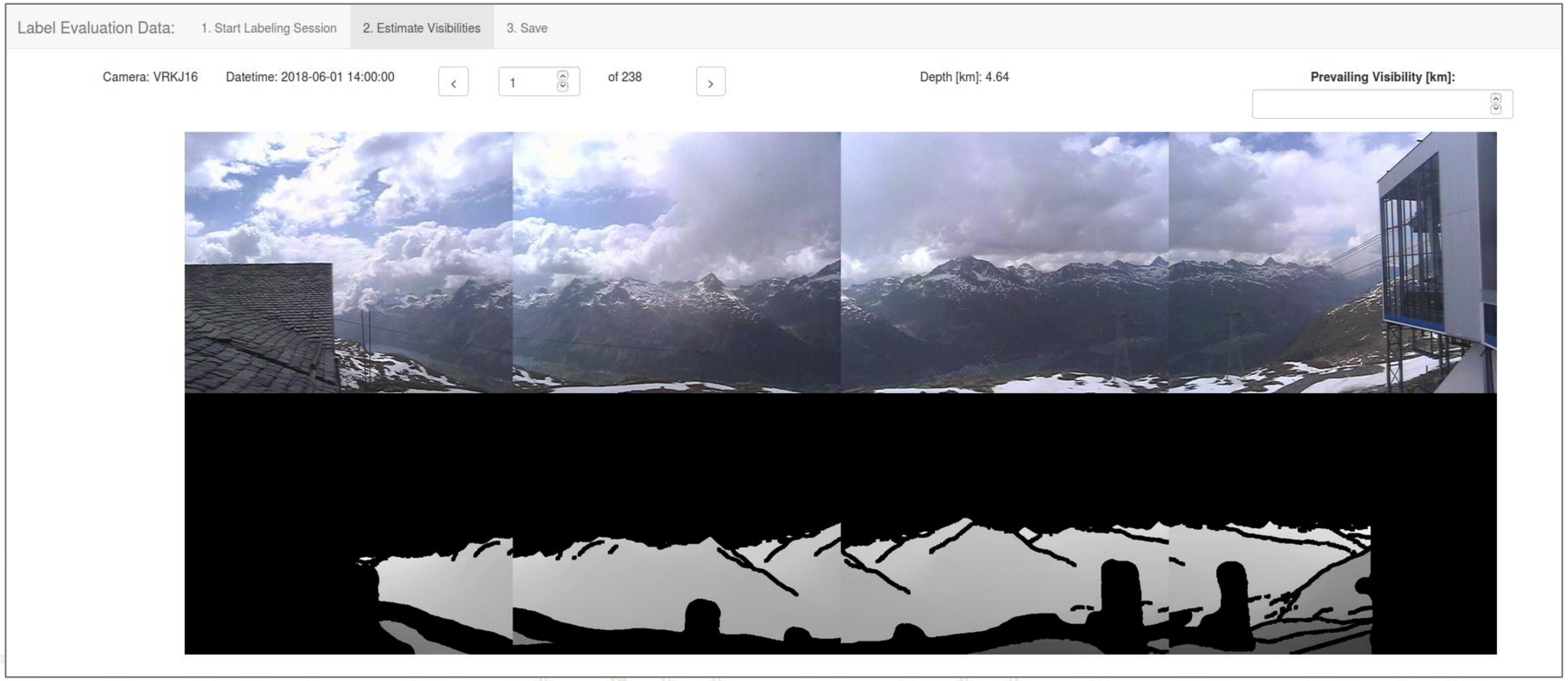
Evaluation Methodology

Comparison with trained observers, labeling the prevailing visibility of panorama sequences:



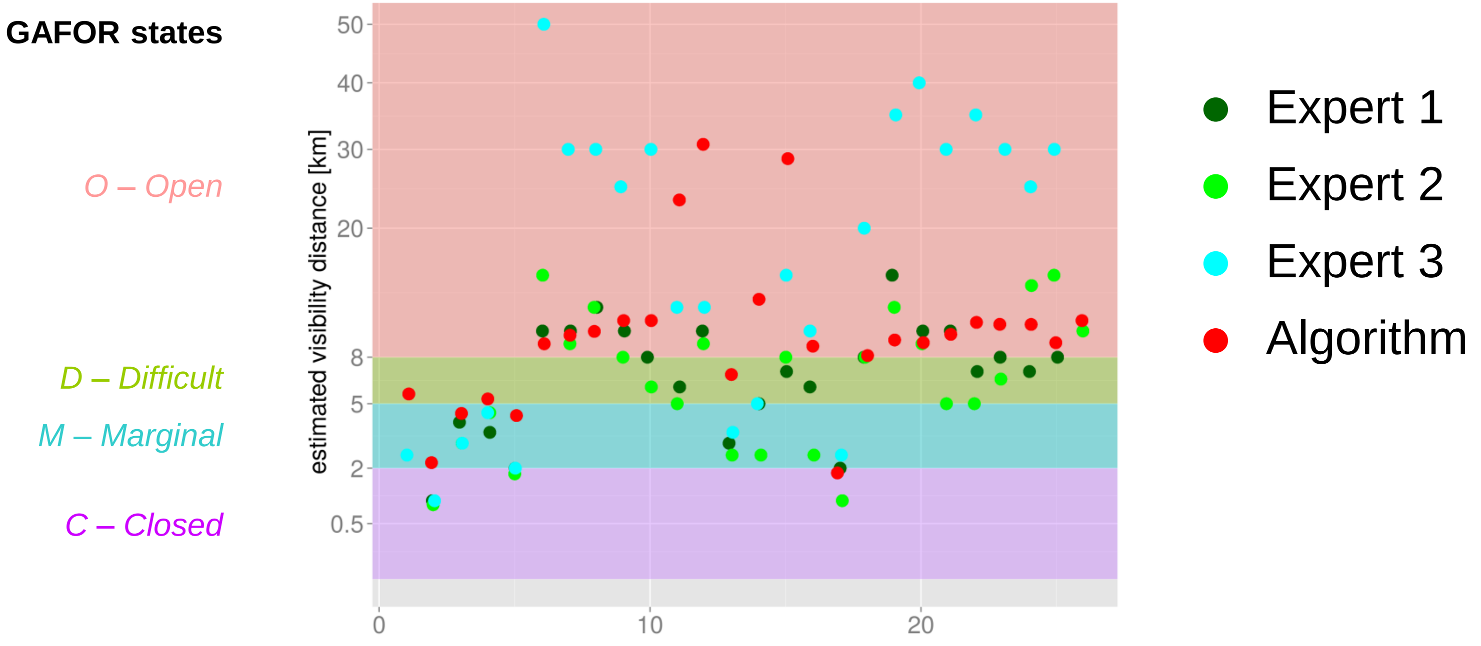
Labeling tool, presenting evaluation sequences in randomized order

Evaluation Data

- 238 panoramic sequences in total
- Representative selection of sites: Swiss plateau, valleys, mountain tops
- Considers all seasons and many different weather and ground conditions

Evaluation Results

In general, algorithmic estimates are within observers' uncertainty:



26 images from the Château d'Oex camera

But there are systematic deviations for certain conditions

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Failure Cases Related to Camera System

Enclosure:

- Mis-alignment of moving head
- Occlusions

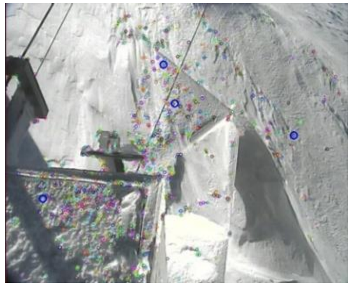

Image acquisition:

- Stray light in lens
- Saturation of dynamic range

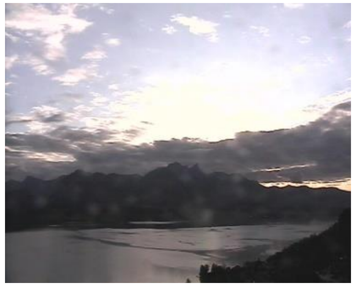

Image processing:

- Compression artefacts
- Artificial edge enhancement

Camera on top of Mount Corvatsch

Renewal of Camera Network

On-going WTO procurement to replace existing cameras:

- Further hardening against weather exposure: increased heating power, mechanical robustness, ...
- Increased sensor dynamic range and resolution
- Raw image acquisition: defined white balance, disabling image “enhancements” (denoising, local contrast enhancement, ...), lossless compression

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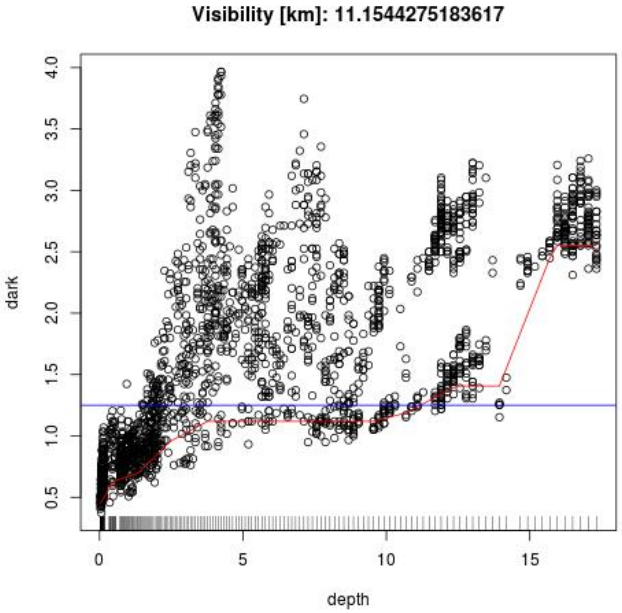
Failure Cases Related to Estimation Algorithm

Complex atmospheric conditions that don't fit the physical model assumptions:

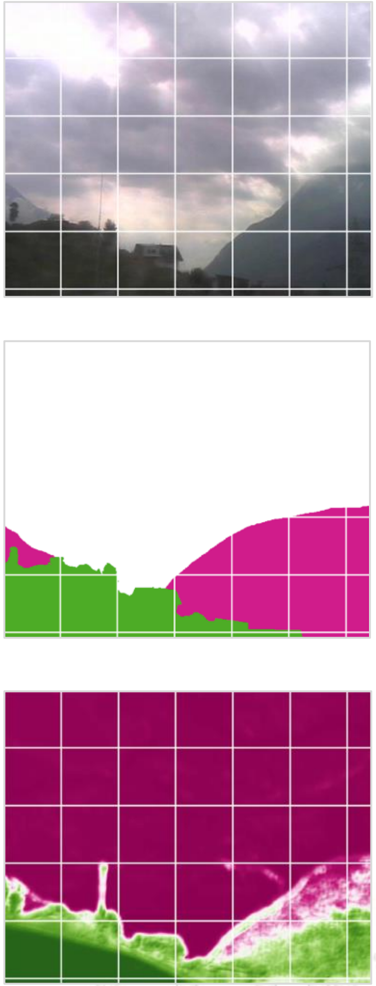


Improvements to Estimation Algorithm

Increase model flexibility with **learning based approach:**

- Neural network classifies pixels as in front or behind the visibility limit
- Expert labels: segmentation into visible and non-visible regions
- Train network to predict label mask

Goal: View independent model, no need for adaptation/tuning to different sites

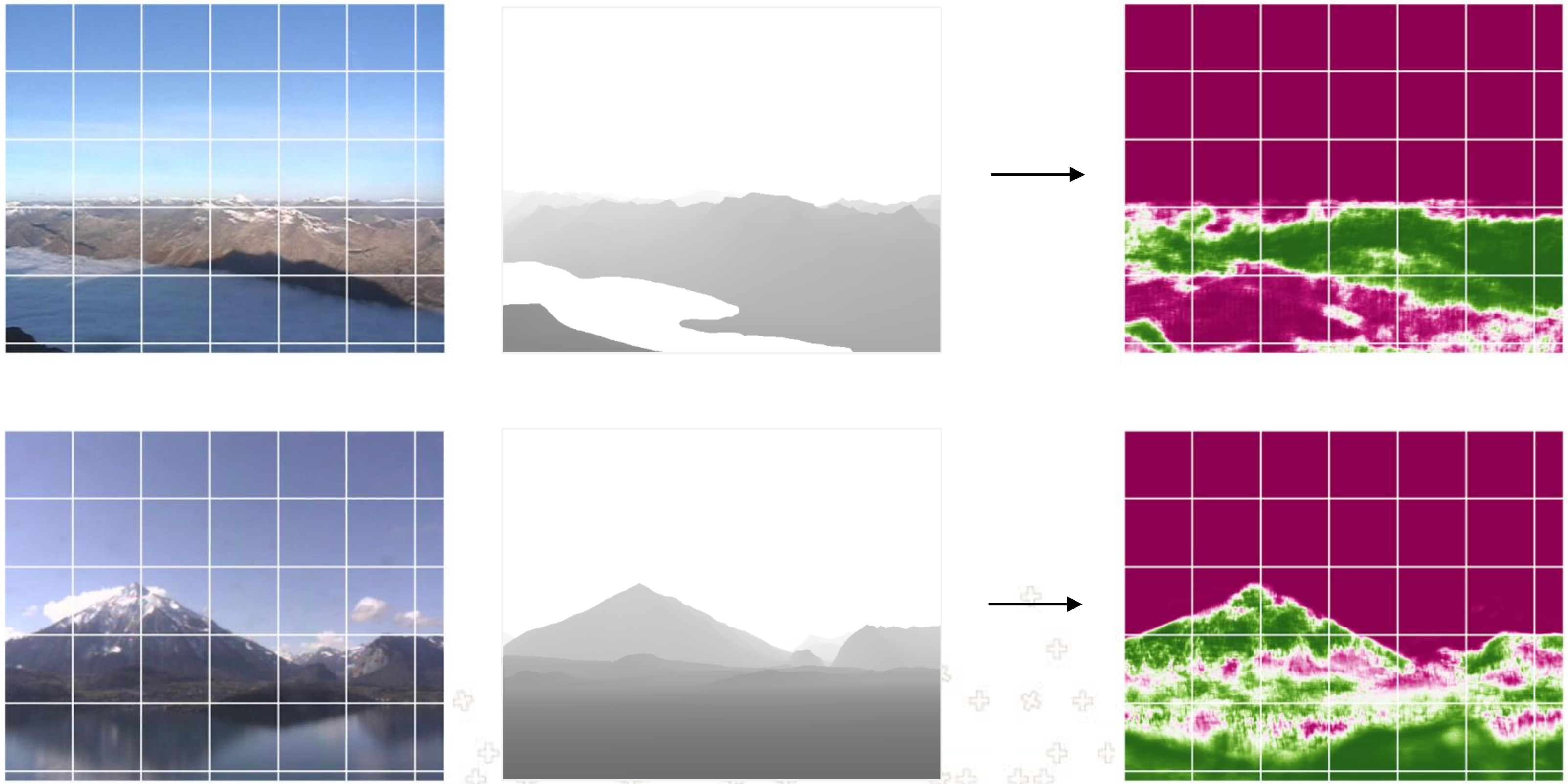


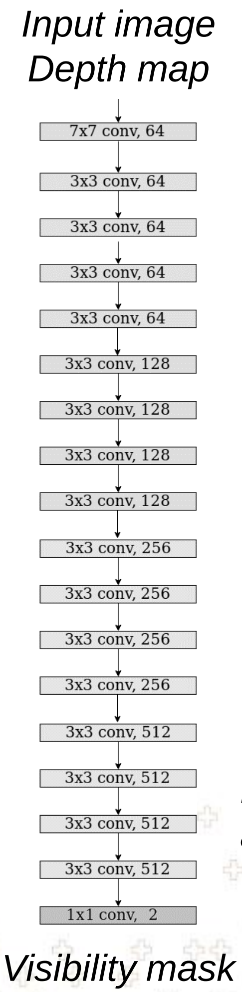
Expert label mask

Prediction

DNN Classifier Architecture

Transformation of input image and depth map across several layers into visibility mask:





ResNet-18 architecture [He *et al.*, 2016]

Summary and Conclusions

- Secondary use of existing infrastructure improves ROI
- Have to compensate for design choices that are not ideal for secondary application

- We have an operational pipeline for visibility estimation
- It takes effort from acceptable performance on average to eliminating all failure cases

- Investment in sensor system pays off at later stages

Summary and Conclusions

Operational availability:

- Monitoring: automated and feedback from users
- Maintenance of cameras, often in remote locations
- Robust software that can deal with various failures: data availability and integrity
- Automated, but still needs personel resources for first, second and third level support

Bibliography

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Koschmieder, H. (1924). *Theorie der horizontalen Sichtweite*. Beitr. Phys. freien Atm., 12:33-53, 171-181.

Sutter, T., F. Nater and C. Sigg (2016). *Camera Based Visibility Estimation*. Proc. CIMO TECO, Vol. 2.