



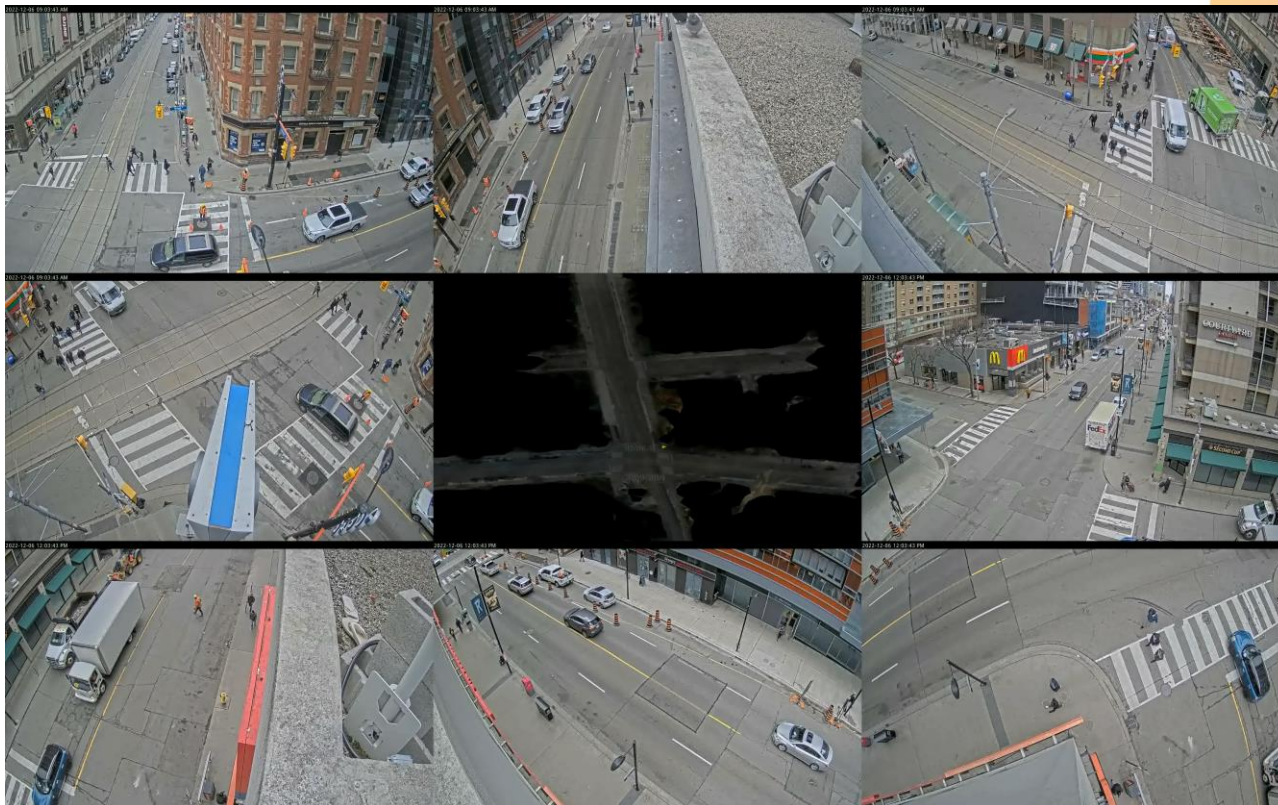
Using a Collaborative Network of Distributed Cameras for Object Tracking

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Invision AI

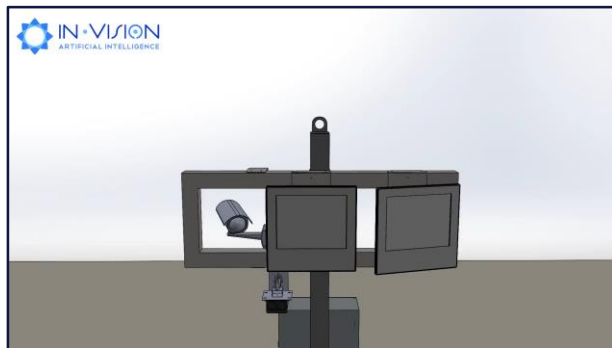
Younge & College: 8 Cameras Outdoors



About Invision AI

Vehicle Occupancy Detection

High-performance Road-side only

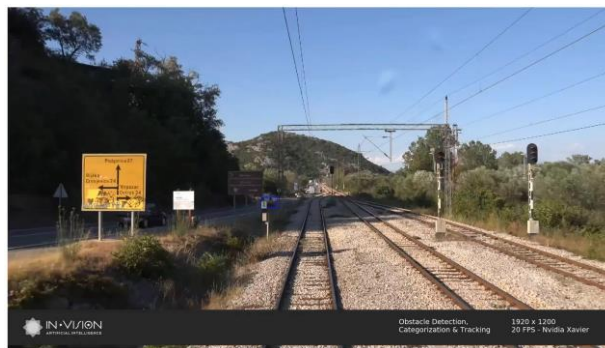


Transurban



Autonomous Rail

Obstacle Detection



THALES



Intersection Monitoring

Hazard Detection



Montréal



Desired Properties of the System

We want our Collaborative Network of Distributed Cameras for Object Tracking to have the following properties:

- Scalability with respect to the number of tracked objects
- Scalability with respect to tracking area
- Reasonable installation constraints (power and network requirements)
- Privacy preserving

Part 1: Mapping and Calibration

Terrain Model and Calibration (Cont'd)

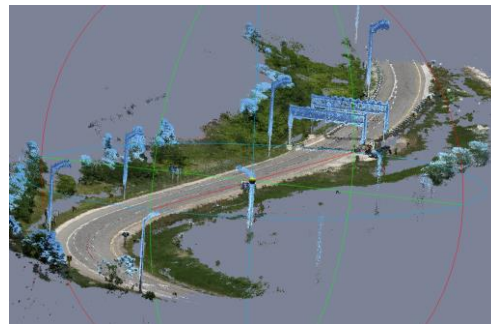
Problems:

1. We need a map.
2. We need to calibrate with respect to the map.

There are two different approaches of how to obtain maps and camera calibrations (camera positions and internal parameters); using structure from motion (SfM) and image matching, or finding already available maps and manually calibrate the cameras.

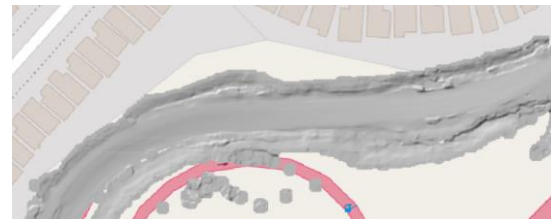
Top-View and Elevation Model From Video

Acquisition



Structure from motion
point cloud (COLMAP,
OpenSfm, OpenMVS)

Top view + digital elevation
model (DEM)



Calibration From Top-View + DEM



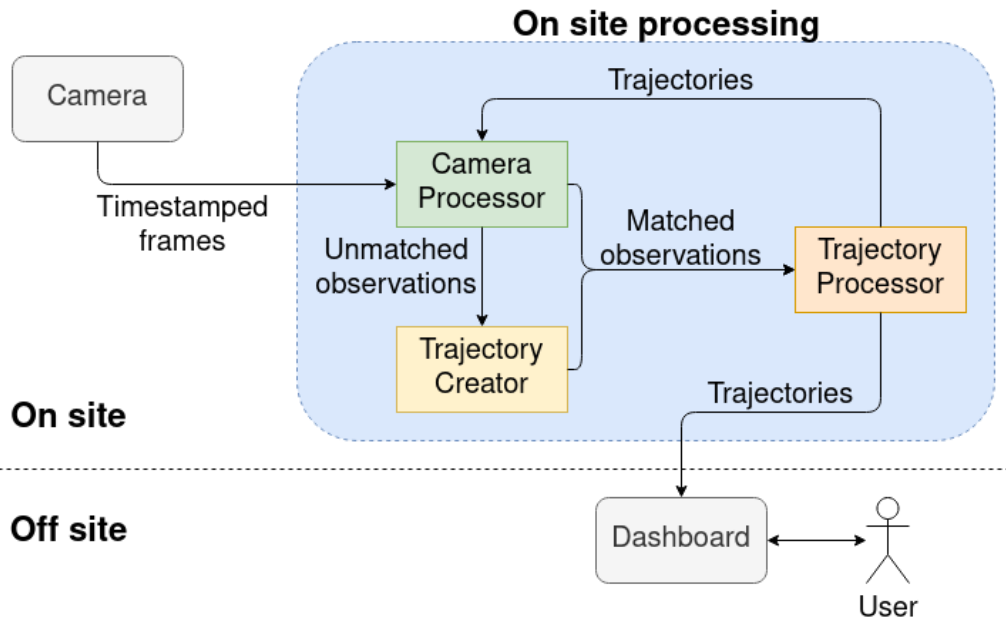
Calibration data links image coordinates with map coordinates.

Swiss coordinate system. Top-view + DEM publicly available.

Part 2: Tracking Algorithm

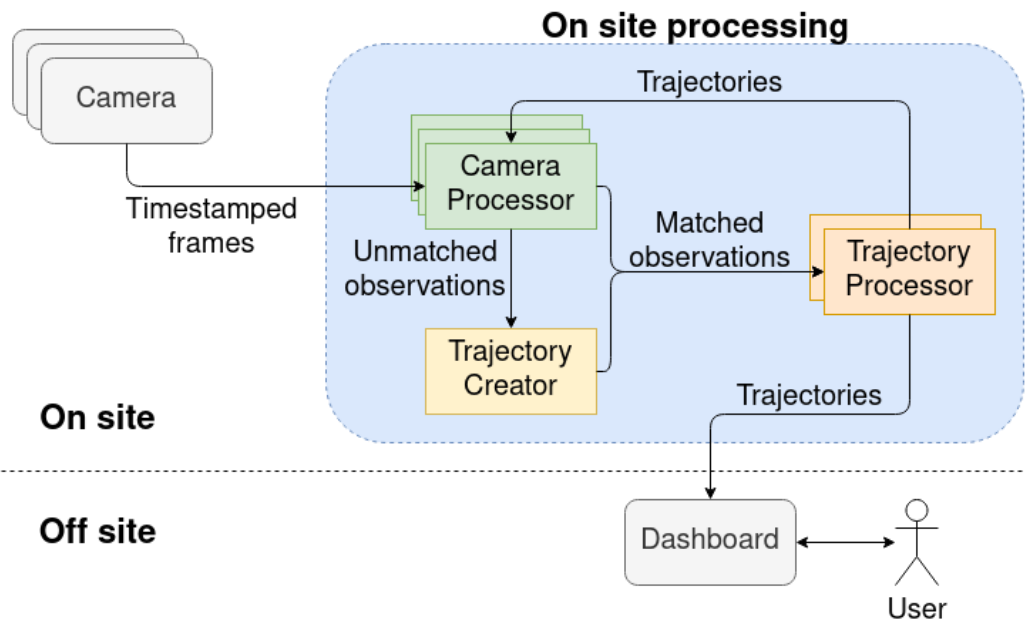
System Overview

- Each processing node is a Unix process.
- Arrows represent inter process communication; can cross machine boundaries.
- Only metadata leaves the deployment site. Image data only travels between camera and camera processor.



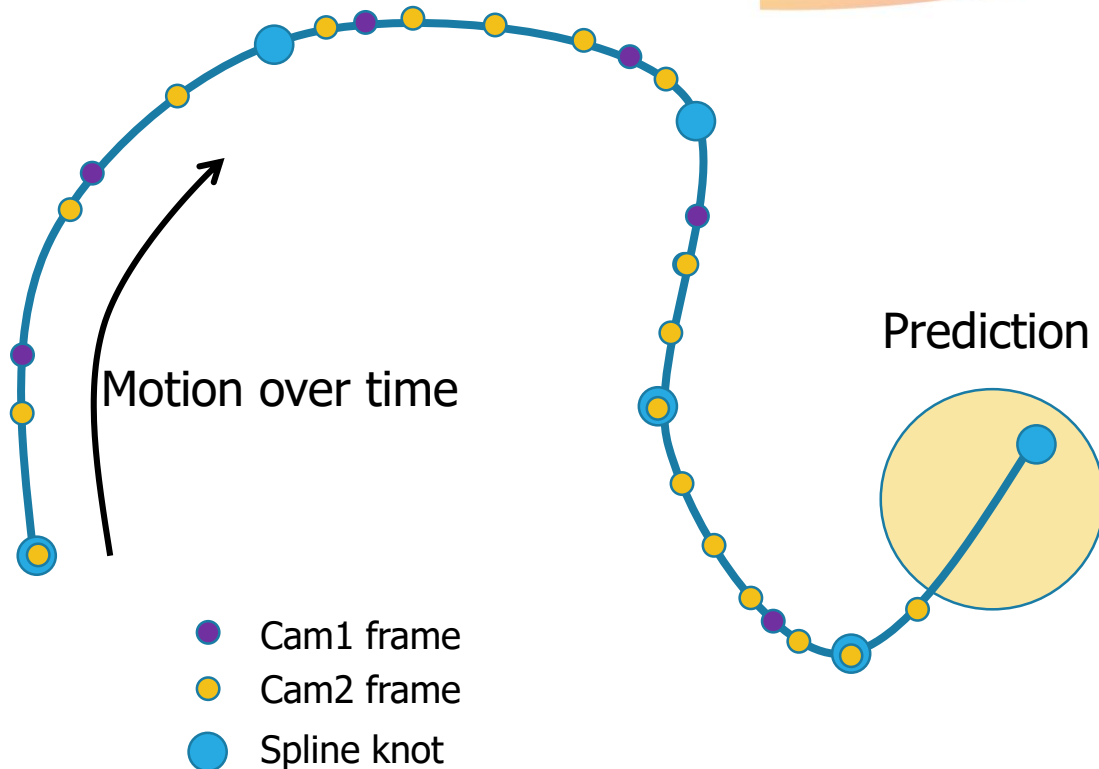
System Overview: How to Scale

- More processing power is obtained by adding more processing nodes.
 - Can be on a new machine.
- Multiple nodes of the same type gives us redundancy; if a processor node breaks (hardware or software), its load can be redistributed, and the system continues to work.



Trajectory Representation

- Trajectory estimated as a spline.
- 1 knot every second.
- Pose (orientation and size) consistency across a track imposed through an on-line non-linear optimization process.
- Able to deal with varying rates of incoming data.
- Predicts motion in the future.



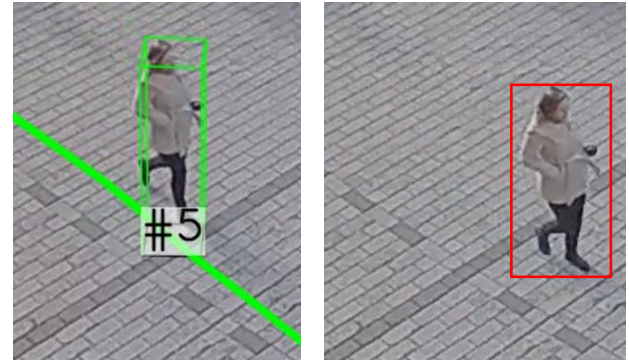
From Observation to Trajectory

Camera processor:

- Produce 2D observations (Neural Net object detector) and associate with trajectories.
- Send association to trajectory processor.

Trajectory processor:

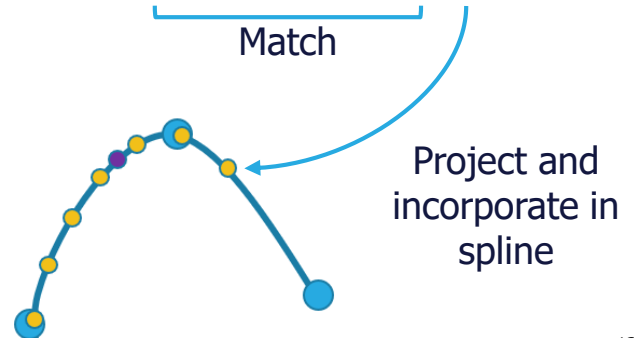
- Project observations (from all views) to common map coordinate system.
- Fusion of all observations + motion model.
- Send updated trajectory back to camera processors.



Trajectory

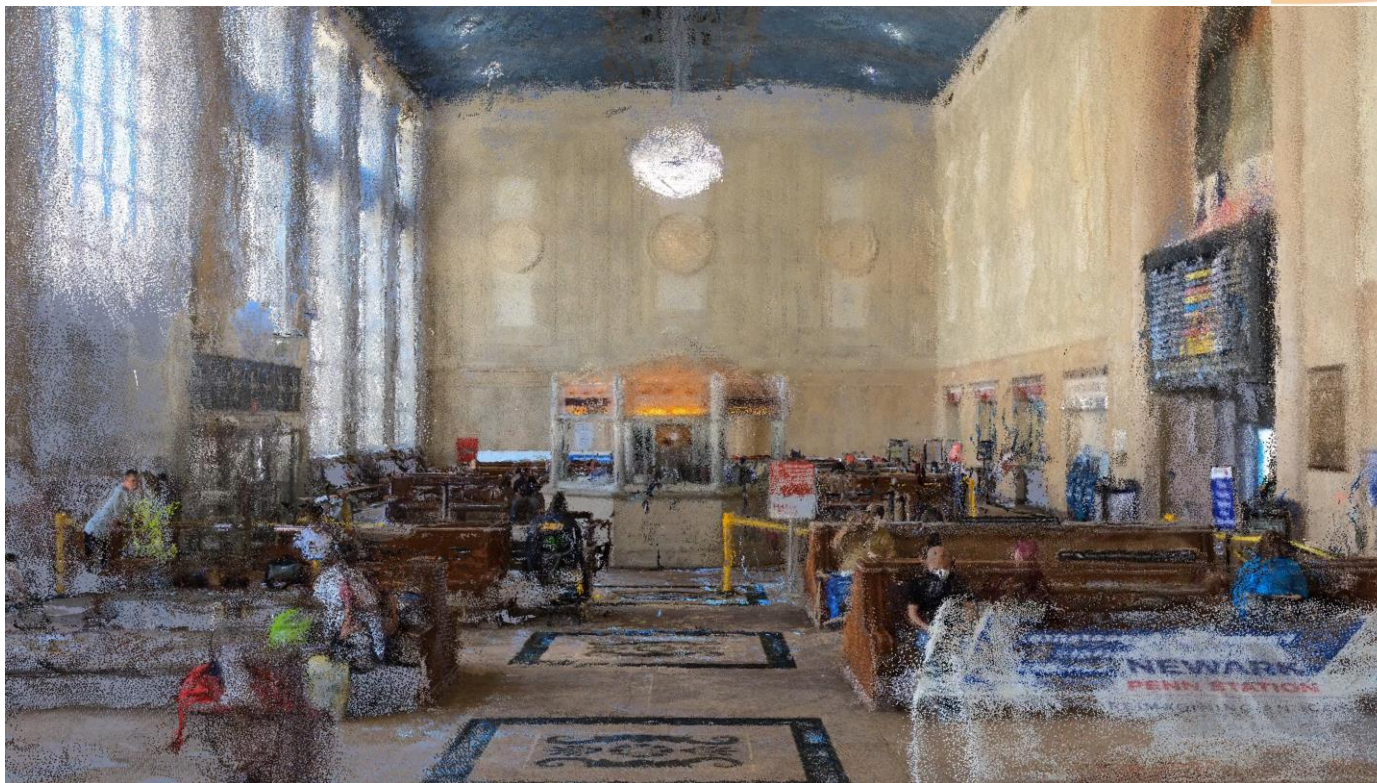
Observation

Match



Part 3: Demos

Demo, 8 Cameras Indoors



Demo, 8 Cameras (Dashboard)

The dashboard features a navigation menu with the following items: Statistics, Heatmap, Trajectories, Counting Geometries, Alerts (Preview), and Help. The 'Trajectories' tab is currently active.

The main interface is divided into two sections:

- Map Region:** A dropdown menu set to '(All)'. Below it is a satellite-style map of Newark Penn Station. The map displays colorful trajectories (green, yellow, red) representing movement paths. Key locations are labeled: 'Platform H', 'Newark Penn Station', 'Newark Penn Station', 'Newark Penn Station', 'Newark Penn Station', 'Top Shelf Annex', 'Row A Slice', and 'Row D Plaza East'. A scale bar indicates 10 meters.
- Table:** A table displaying object detection results. The columns are: Start, End, Object type, Face Mask, F.M. Confidence, and Sort. The table contains 10 rows of data, with the first row selected. A 'Search' button and an 'Export' button are located to the right of the table. At the bottom of the table, there is a pagination control showing '1' selected out of 1000 items, with 'Next' and 'Previous' arrows.

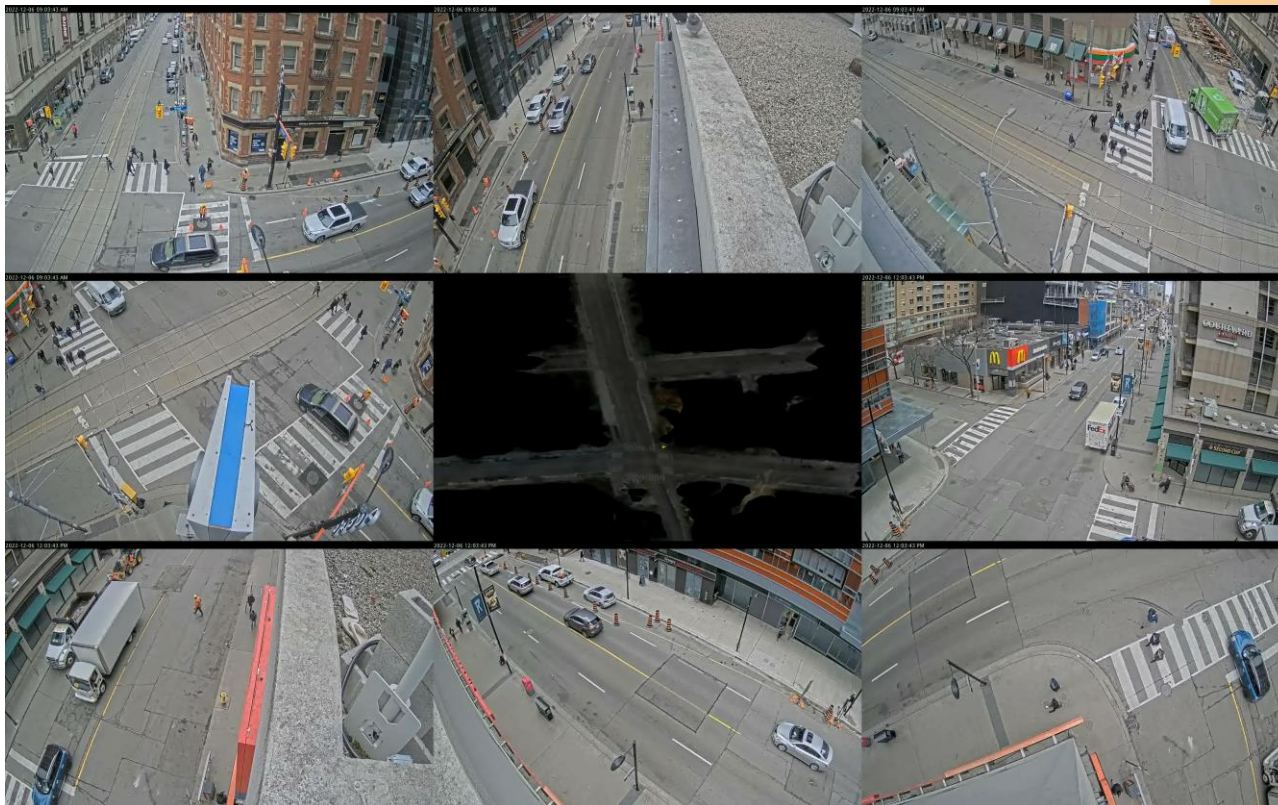
Start	End	Object type	Face Mask	F.M. Confidence	Sort: ▲ Stz ▼
2022-06-07 07:00:00 - 2022-06-09 20:00:00					Search
2022-06-07 06:58:25	2022-06-07 07:00:28	Person	Has Mask	0.97	Export
2022-06-07 06:58:54	2022-06-07 07:00:04	Person	No Mask	0.86	
2022-06-07 06:59:11	2022-06-07 07:00:16	Person	Has Mask	0.70	
2022-06-07 06:59:23	2022-06-07 07:01:33	Person	No Mask	0.90	
2022-06-07 06:59:33	2022-06-07 07:00:01	Person	Unknown	1.00	
2022-06-07 06:59:41	2022-06-07 07:00:17	Person	Has Mask	0.68	
2022-06-07 06:59:41	2022-06-07 07:00:14	Person	No Mask	0.98	
2022-06-07 06:59:42	2022-06-07 07:00:02	Person	Has Mask	0.70	
2022-06-07 06:59:42	2022-06-07 07:00:02	Person	Has Mask	0.70	

Remaining Challenges and Conclusion

Questions and Challenges

- Installation constraints means it is not always possible to use a wired network:
 - Could we do networking with radio + mesh network?
- The system needs a lot of compute; how to get a low energy, affordable NN inference system?
 - Anything else than NVidia Jetson products?
- Calibration of the system is time consuming. Are there better solutions out there for automatic calibration?

Conclusion



References and resources

Software and libraries

COLMAP

<https://colmap.github.io/>

OpenSfM

<https://opensfm.org/>

PDAL

<https://pdal.io/>

Contact us!

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