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Using space-time cube for visualization of active transportation patterns derived from public webcams

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Public webcams

Rich source of spatio-temporal information

- weather, traffic, changes in environment, phenology, ...
- active transportation behavior in urban areas

AMOS

The Archive of Many Outdoor Scenes

- collection of long-term timelapse imagery from publicly accessible outdoor webcams around the world
- 1,128,087,180 images taken from 29945 webcams
- a project of the Media and Machines Lab Washington University in St. Louis
- online browsing of images and download available
- metadata and tags to improve discoverability of webcams

From image to information

How to get from image to information useful for analysis?

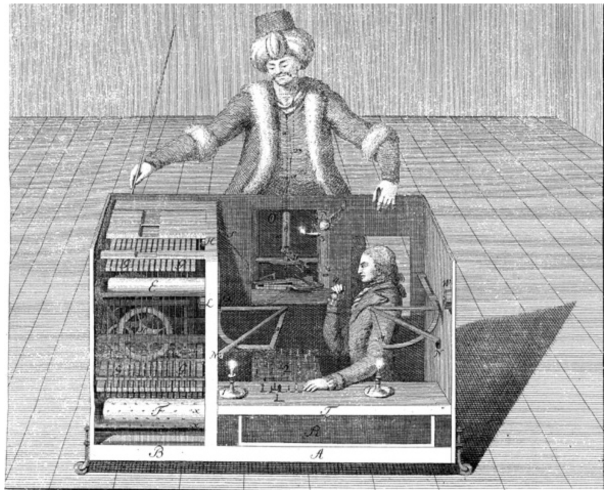
Artificial intelligence

- machine learning
- neural networks

https://xkcd.com/1838

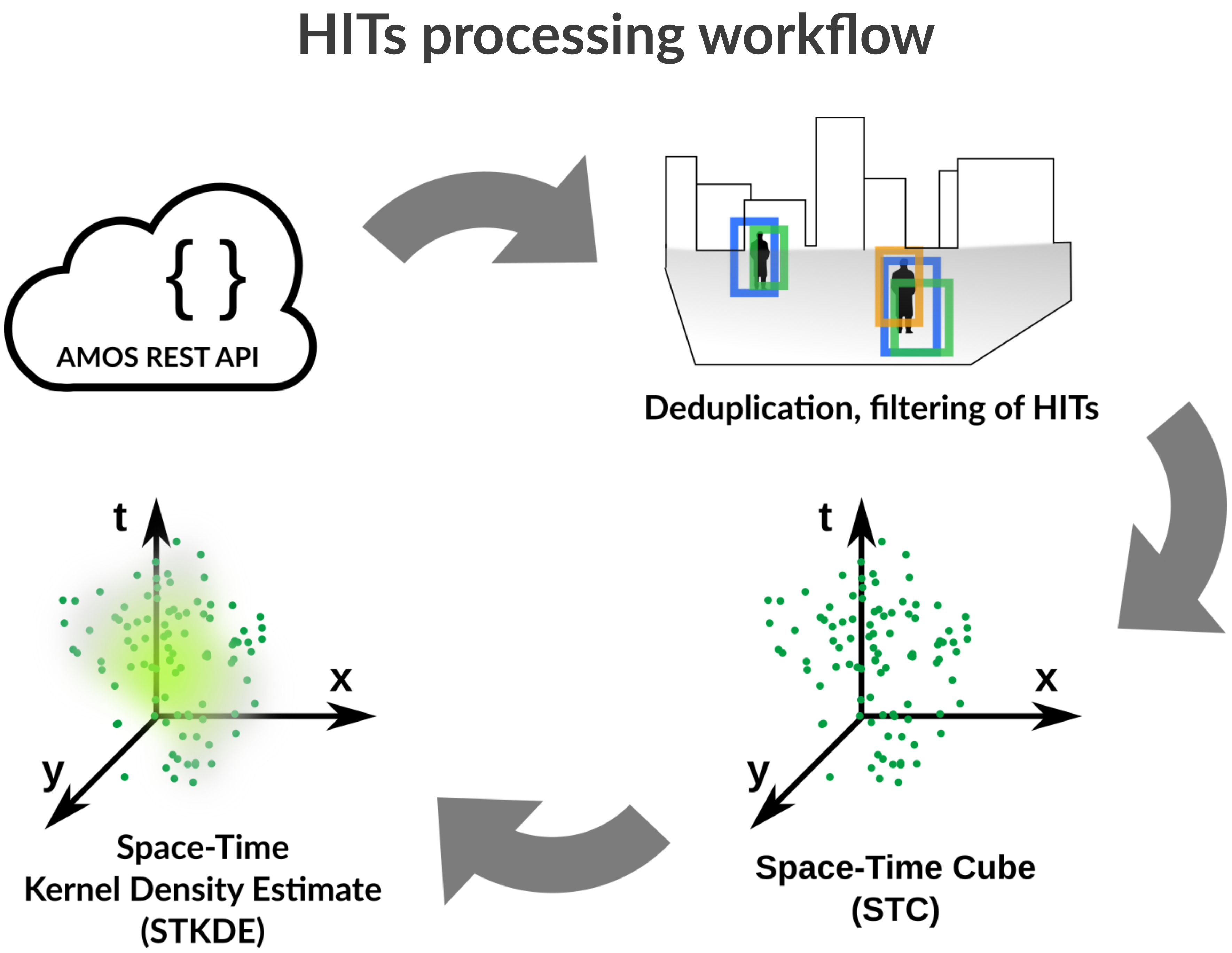
Artficial artficial intelligence

- Amazon Mechanical Turk
- crowdsourcing marketplace platform



fake chess-playing machine (lat e 18th century)

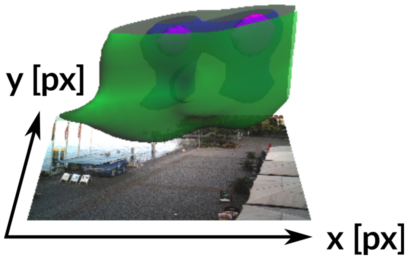
mTurk HITs (Human Intelligence Tasks)


HITs processing workflow
{ }
AMOS REST API
Deduplication, filtering of HITs
t
x
y
Space-Time
Kernel Density Estimate
(STKDE)
t
x
y
Space-Time Cube
(STC)

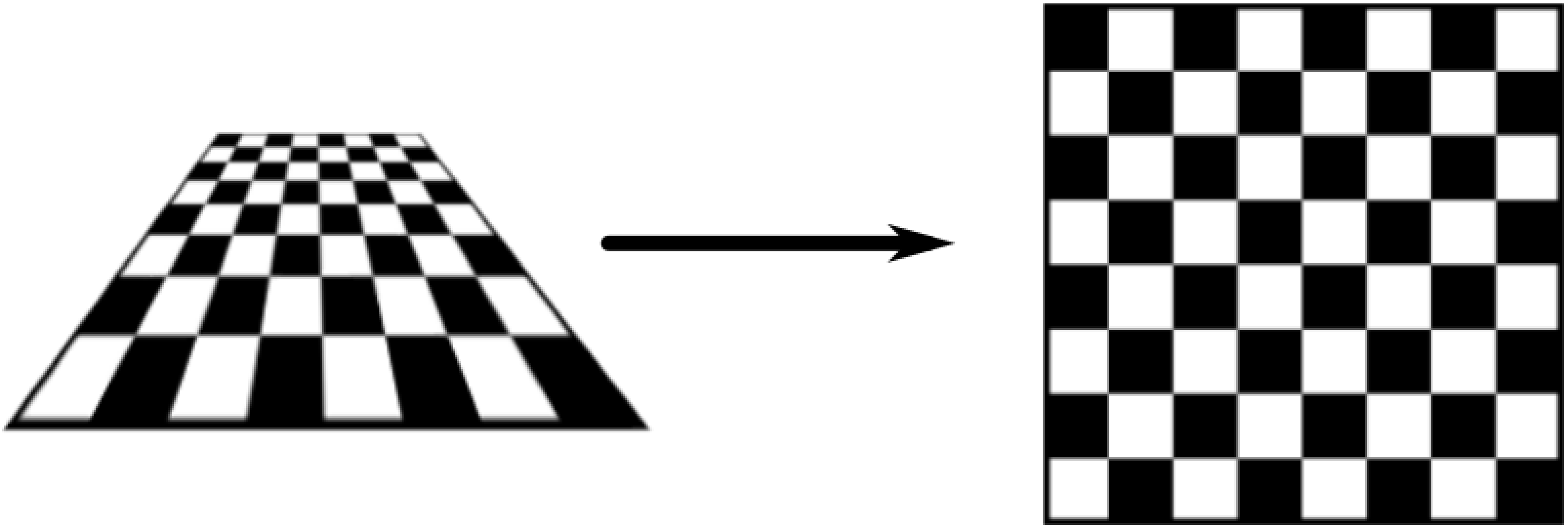
Georeferencing

Using coordinate system of the webcam image:

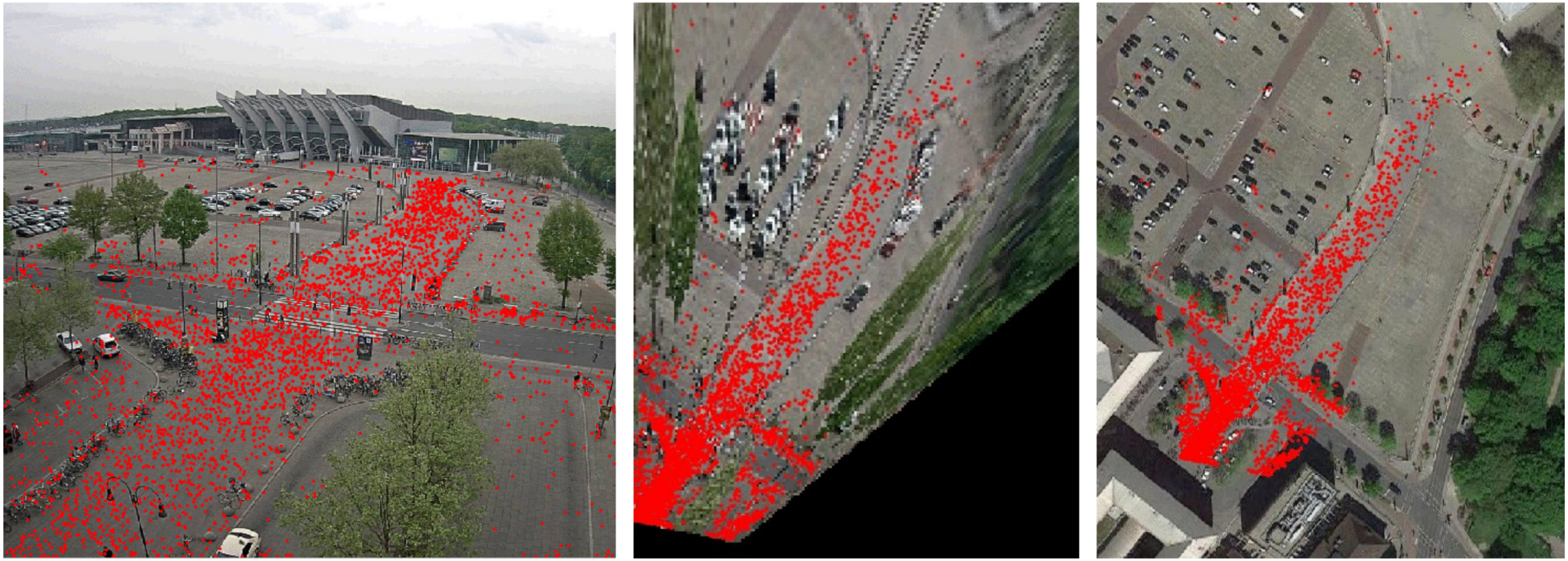
- distances in the image represent varying distances in reality
- we can't integrate other geospatial datasets (streets, POIs) or information from other webcams



Solution is to compute **projective transformation** by matching 4+ stable features in the webcam image to the same features in the orthophoto.



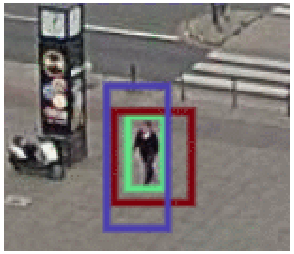
Georeferencing: example

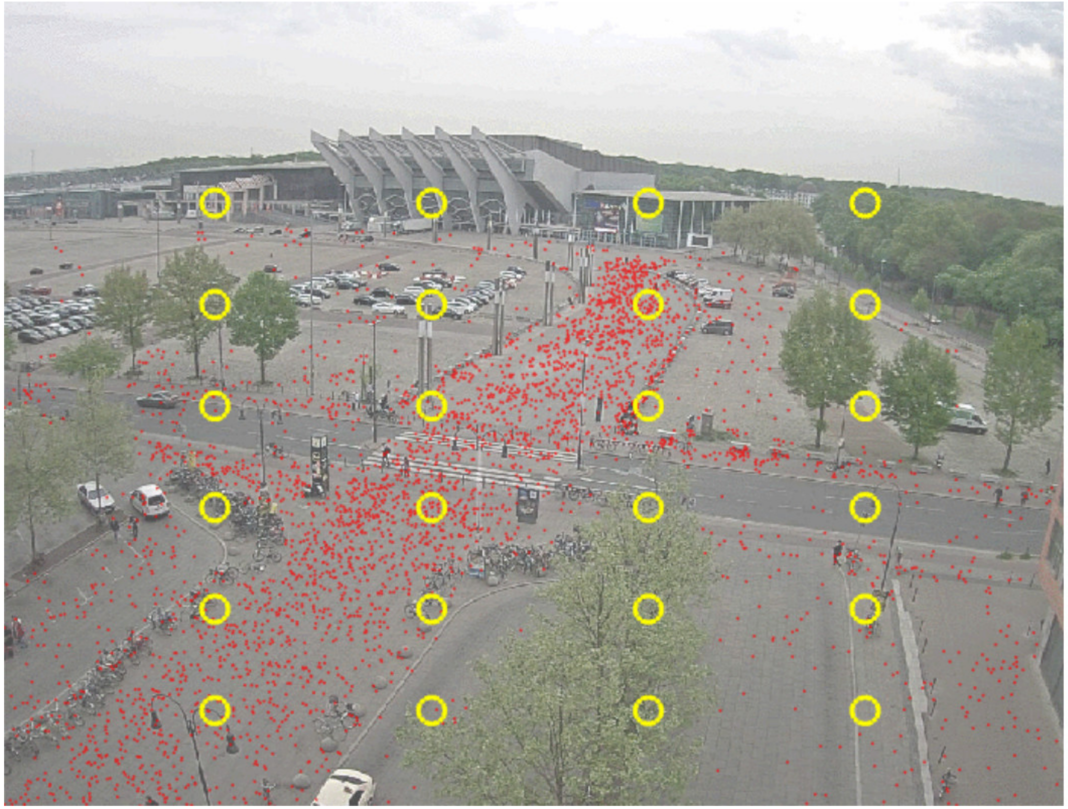


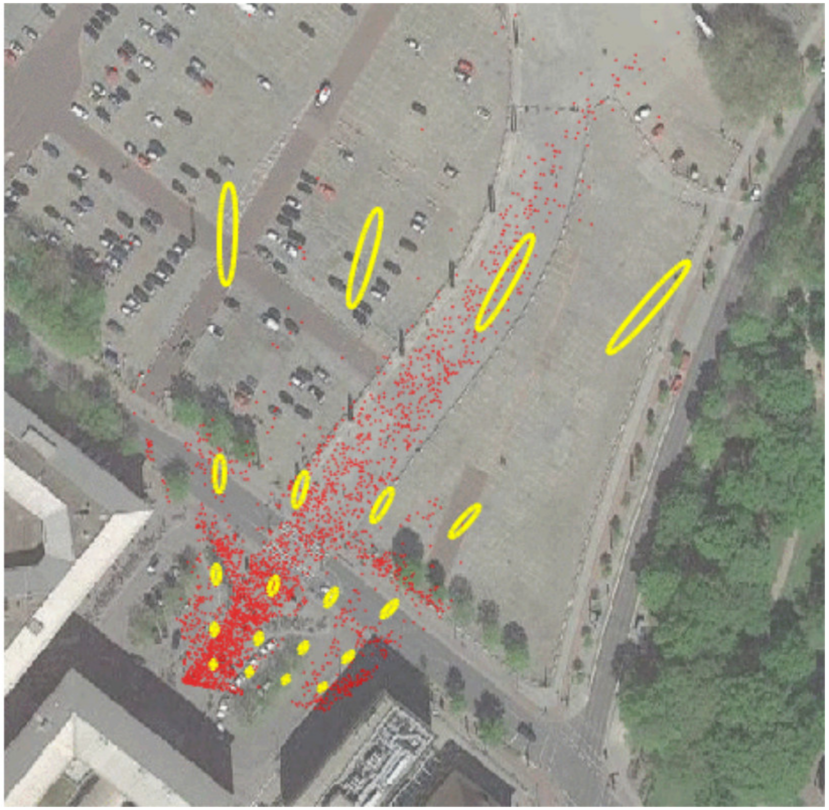
Caveats: some webcams change orientation, many objects such as benches, traffic marking are unsuitable as GCPs, stable objects such as statues can move too

Distortions

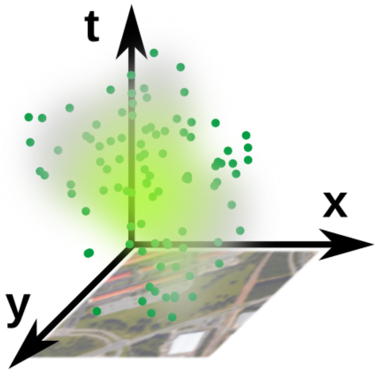
Small errors in the mTurk outlines result in large spatial errors further from the webcam





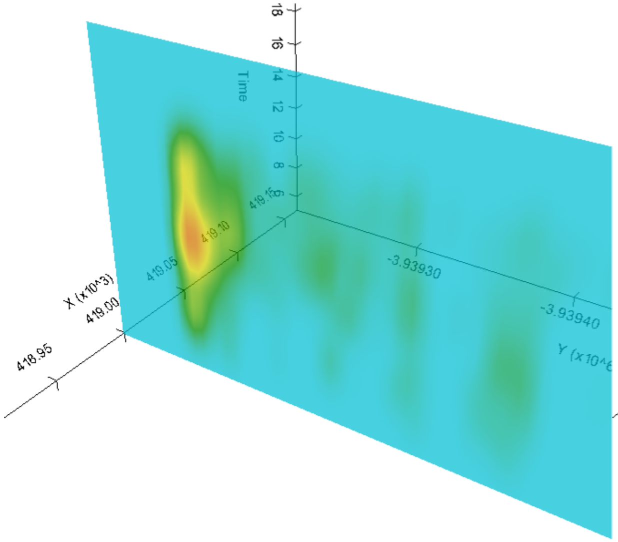


STC visualization

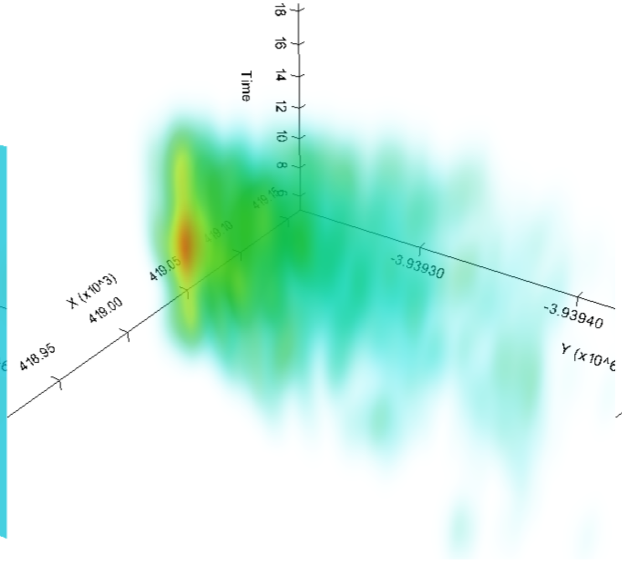


Space-time density of pedestrians represented as a 3D volume, computed using multivariate Kernel Density Estimation (KDE) with different spatial and temporal bandwidths

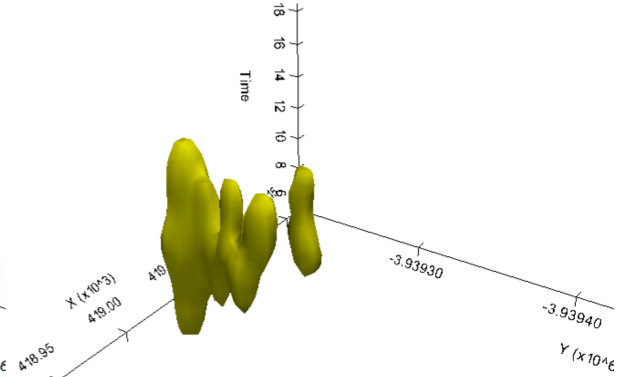
slice



volume rendering

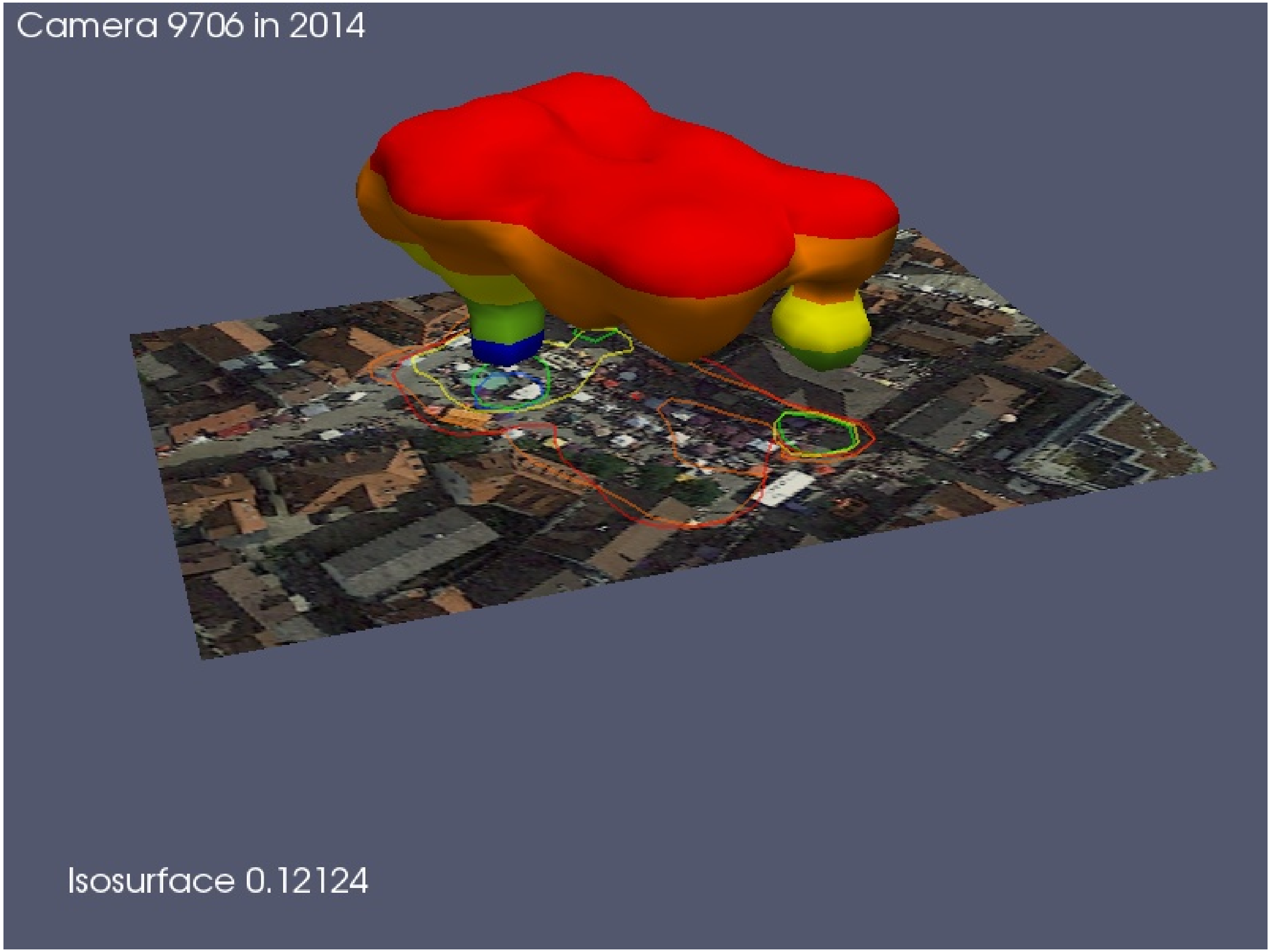


isosurface



Pedestrian density visualization

webcam 9706 (July), Ehingen, Germany



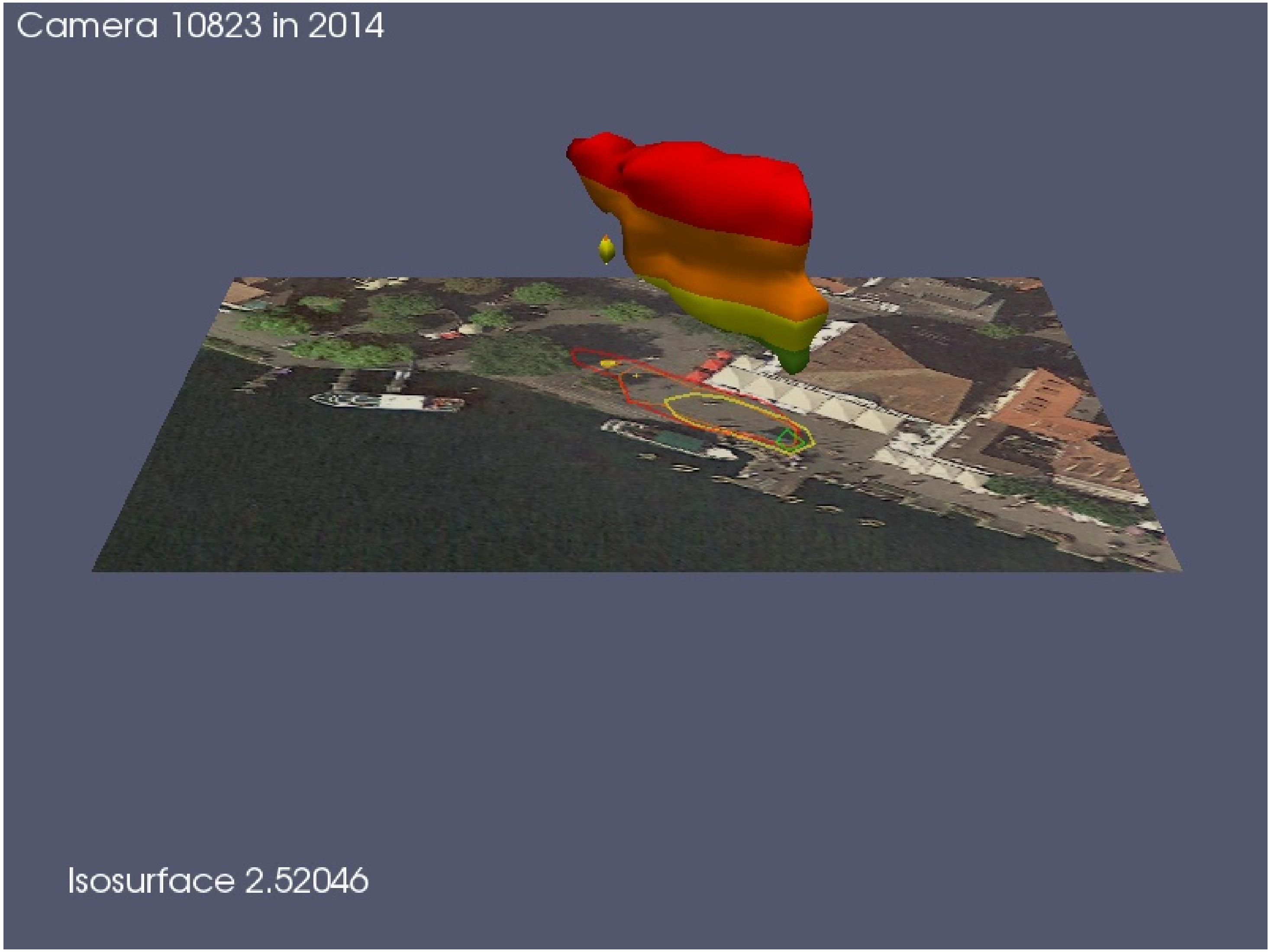
- evening (after 5 pm)
- afternoon (1 - 5 pm)
- noon (11 am - 1 pm)
- morning (9 - 11 am)
- before 9 am

Isosurface (people per 100 m^{2}h)

Rotate

Pedestrian density visualization

webcam 10823 (July), Überlingen, Germany



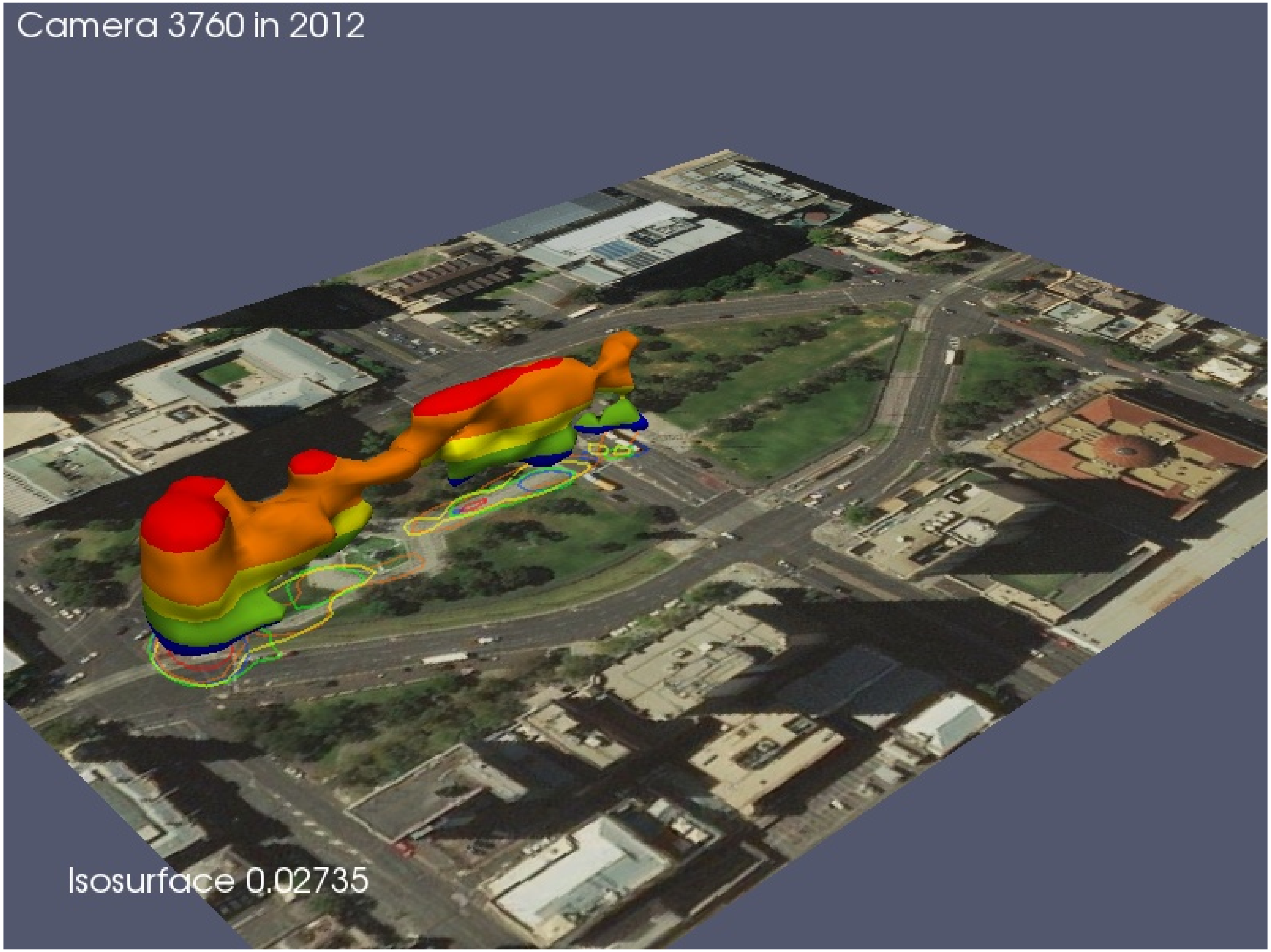
evening (after 5 pm)
afternoon (1 - 5 pm)
noon (11 am - 1 pm)
morning (9 - 11 am)
before 9 am

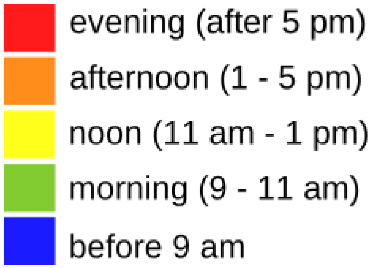
Isosurface (people per 100 m^2h)

Rotate

Effects of plaza reconstruction

webcam 3760 in 2012 (Jul - Sep), Victoria Square, Adelaide, Australia



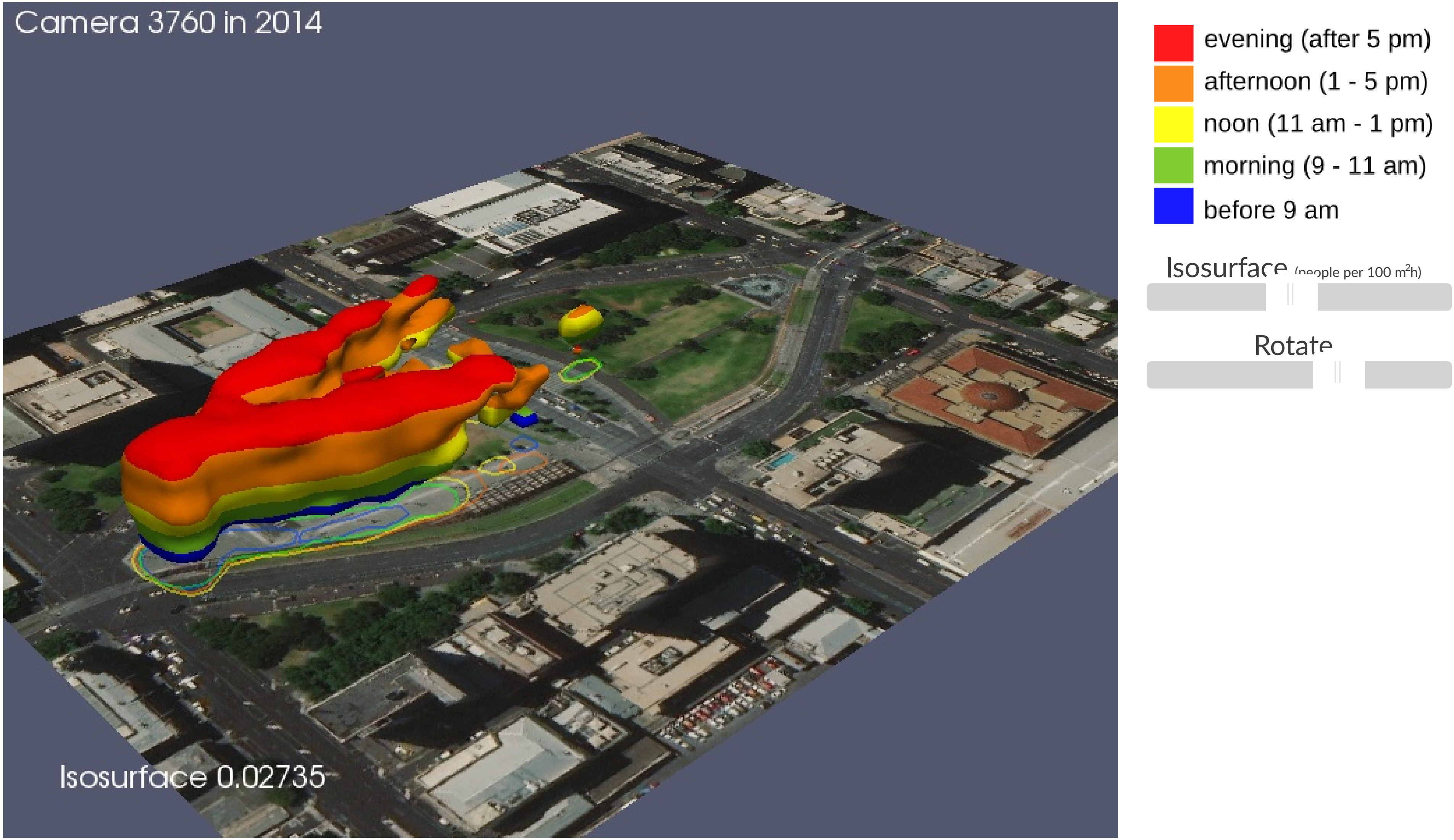


Isosurface (people per 100 m²h)

Rotate

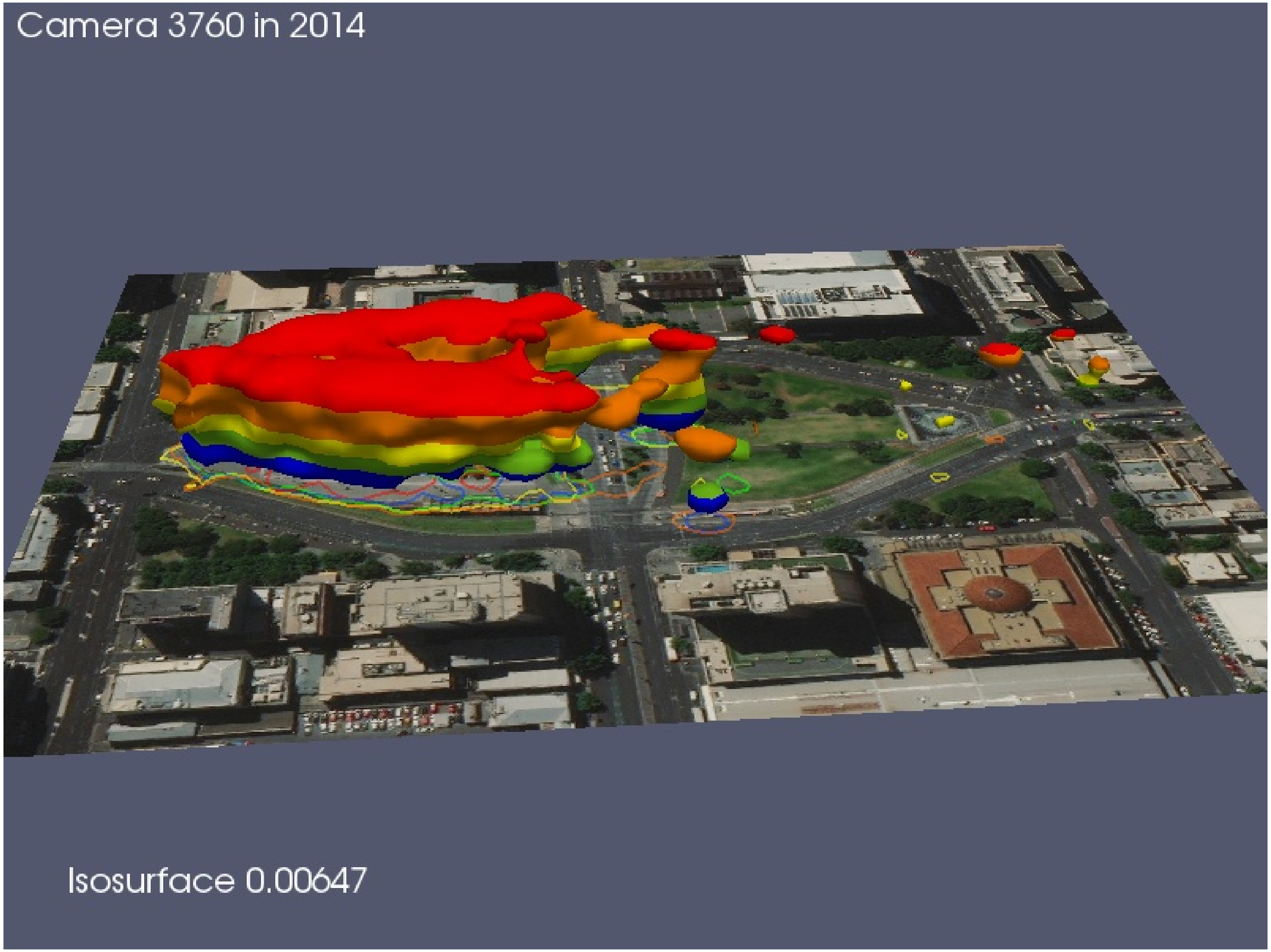
Effects of plaza reconstruction

webcam 3760 in 2014 (Jul - Sep), Victoria Square, Adelaide, Australia



Change in pedestrian density (2014 minus 2012)

Positive values ~ increase in density in 2014
Negative values ~ decrease in density in 2014



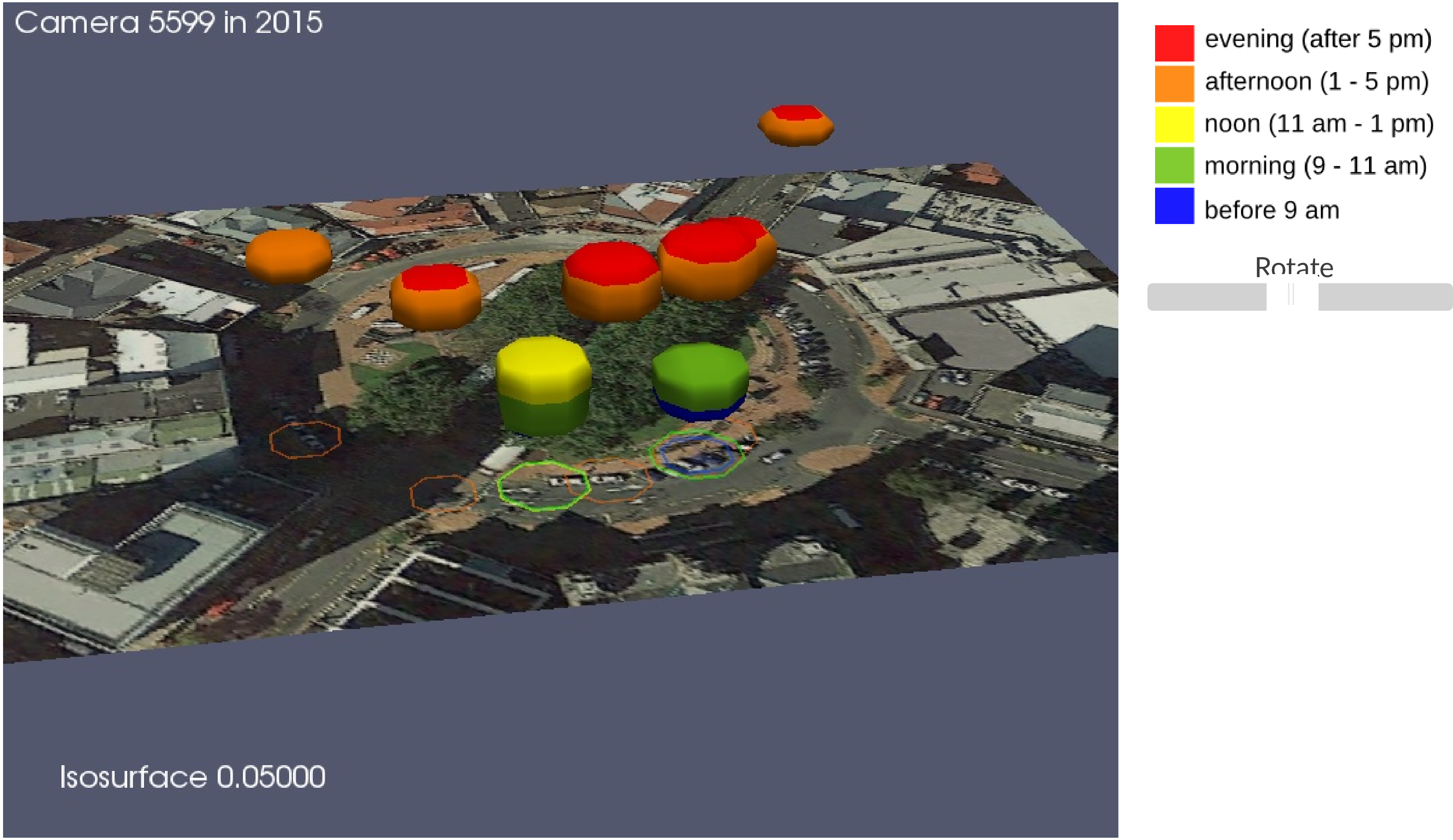
evening (after 5 pm)
afternoon (1 - 5 pm)
noon (11 am - 1 pm)
morning (9 - 11 am)
before 9 am

Isosurface (people per 100 m^{2}h)

Rotate

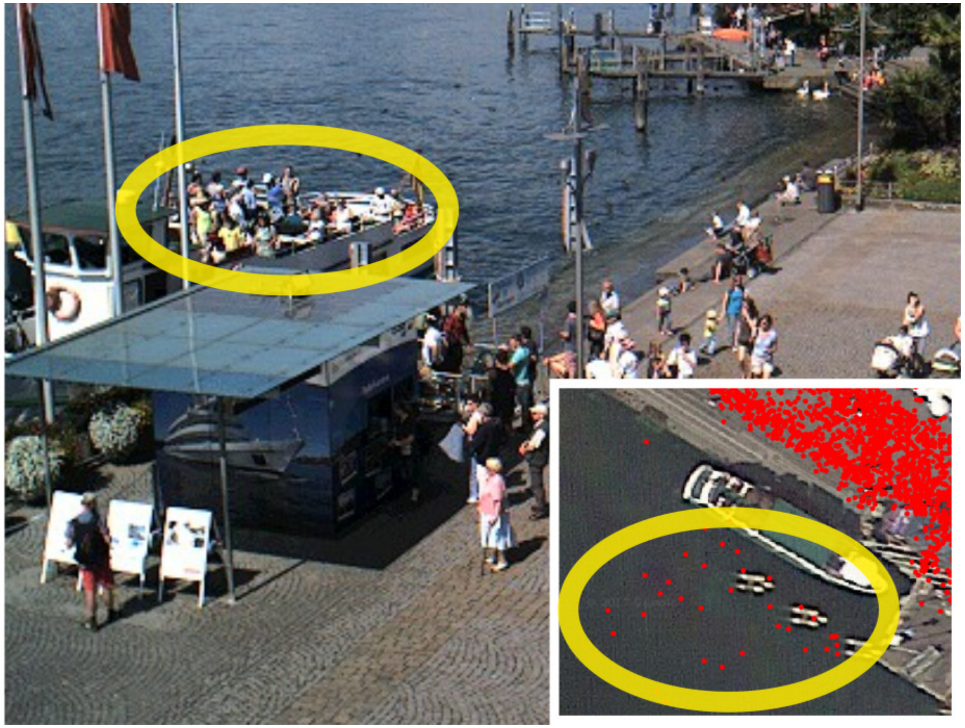
High density of pedestrians and vehicles (webcam 5599)

$$\texttt{if (P > percentile}^{P}_{99}\texttt{ AND V > percentile}^{V}_{99}\texttt{, V + P)}$$



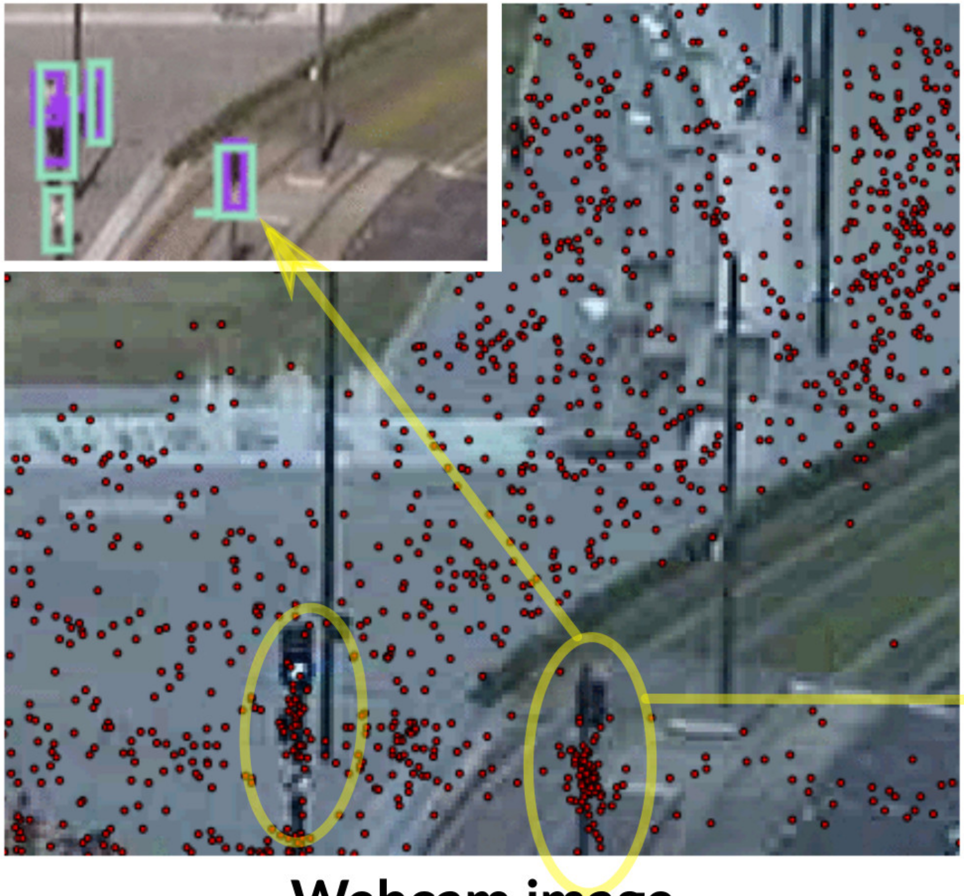
Challenges: webcam geometry and view

- areas hidden behind trees or other objects
- assumes pedestrians and vehicles on a horizontal plane, otherwise we get large spatial errors

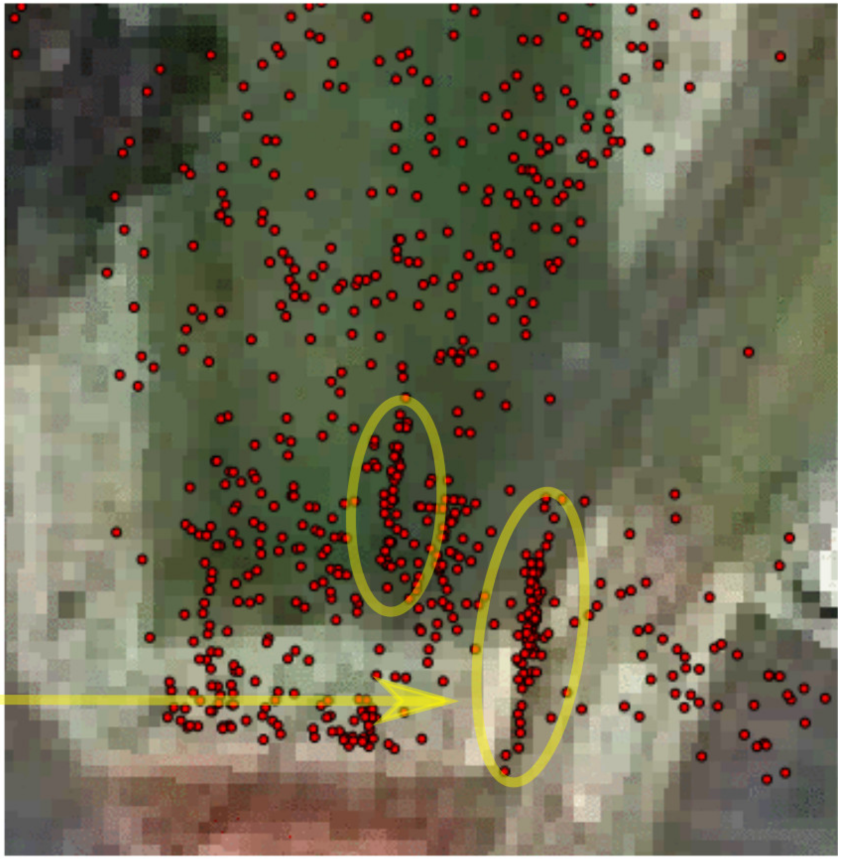


Challenges: mTurk reliability

Traffic lights, statues mistakenly marked as pedestrians, machine learning approaches would avoid this type of error



Webcam image



Georeferenced

Software

- Python libraries
- Jupyter Notebook for data exploration
- Georeferencing: scikit-image, GRASS GIS
- KDE: SciPy, Statsmodels
- Rendering: ParaView, GRASS GIS

github.com/petrasovaa/amos-visualization

Conclusion & Future work

- new method for **harvesting and visualization** of spatio-temporal information about active transportation
- new way for cities to **detect and analyze changes** in active transportation behavior in an unintrusive way
- georeferenced data give us the ability to **incorporate other geospatial data and methods** (e.g., solar radiation modeling)
- possible thanks to the **synergy between crowdsourcing** technologies (AMOS, mTurk, open source software)
- **machine learning** techniques trained by mTurk data will enable us to analyze much **larger data** volume in real-time, possibly leading to the discovery of more patterns

References:

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