FOSS4G 2017

Visualization and analysis 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?

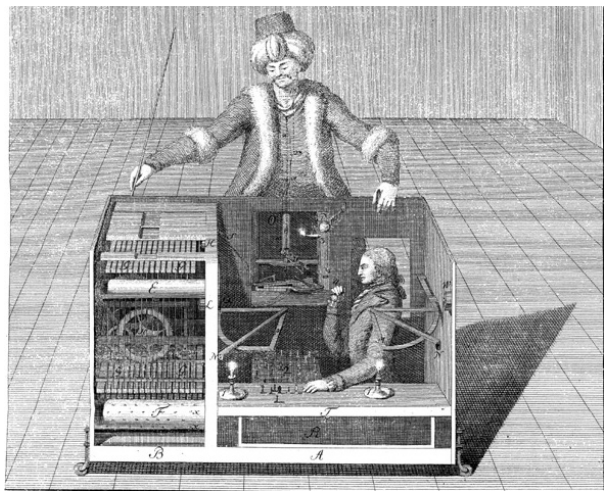
Artificial intelligence

- machine learning
- neural networks

https://xkcd.com/1838

Artficial artficial intelligence

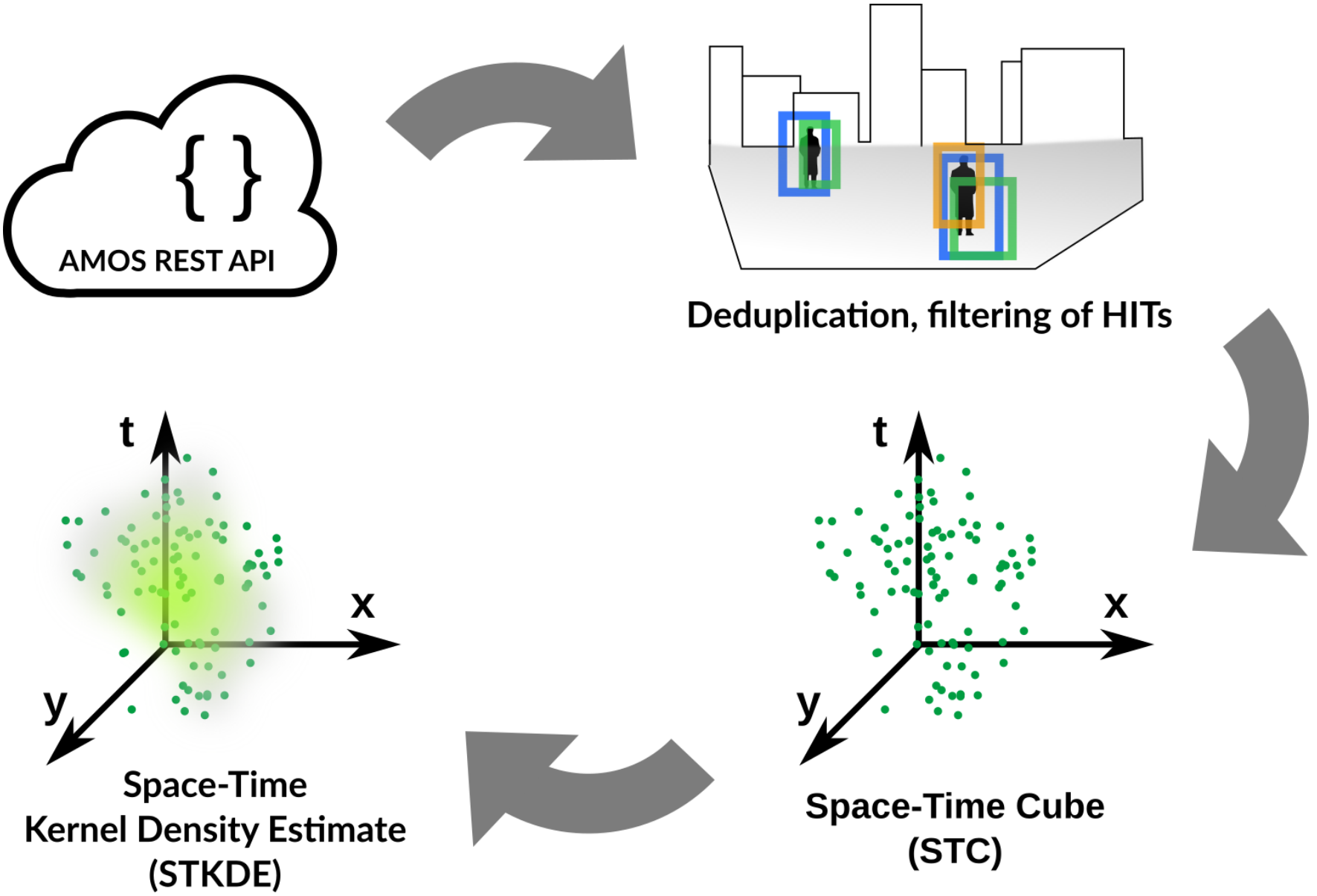
- Amazon Mechanical Turk
- crowdsourcing marketplace platform



fake chess-playing machine (late 18th century)

mTurk HITs (Human Intelligence Tasks)

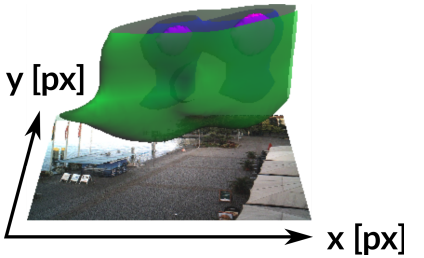
HITs processing workflow



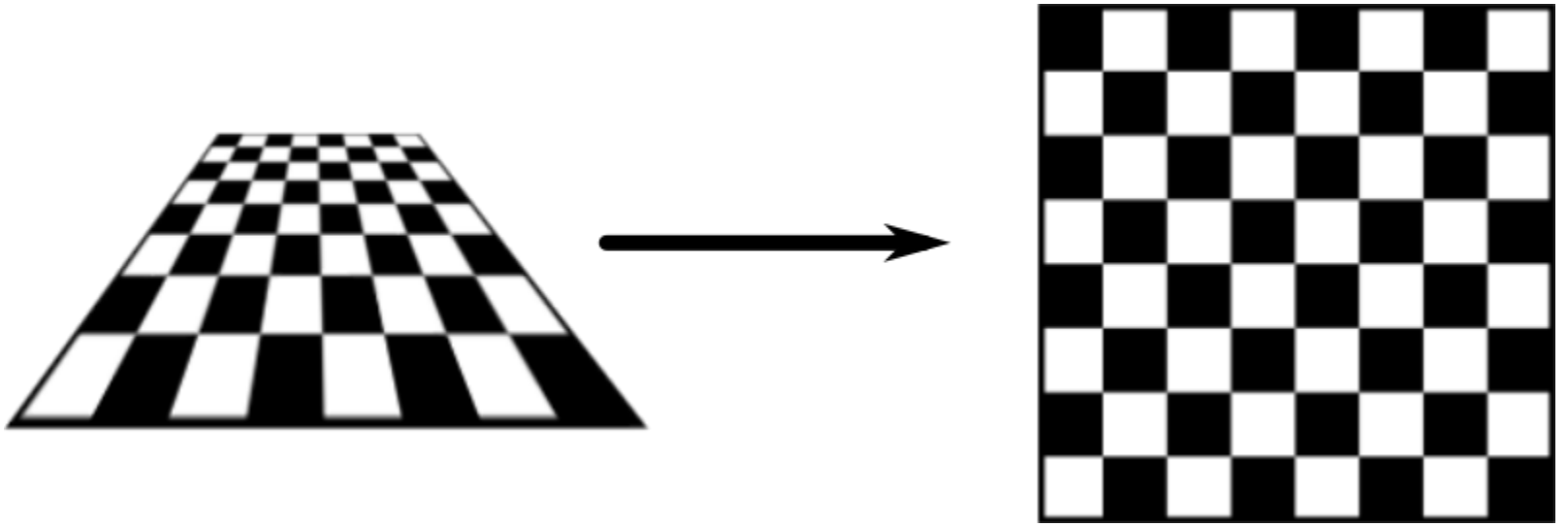
Georeferencing

Using coordinate system of the webcam image:

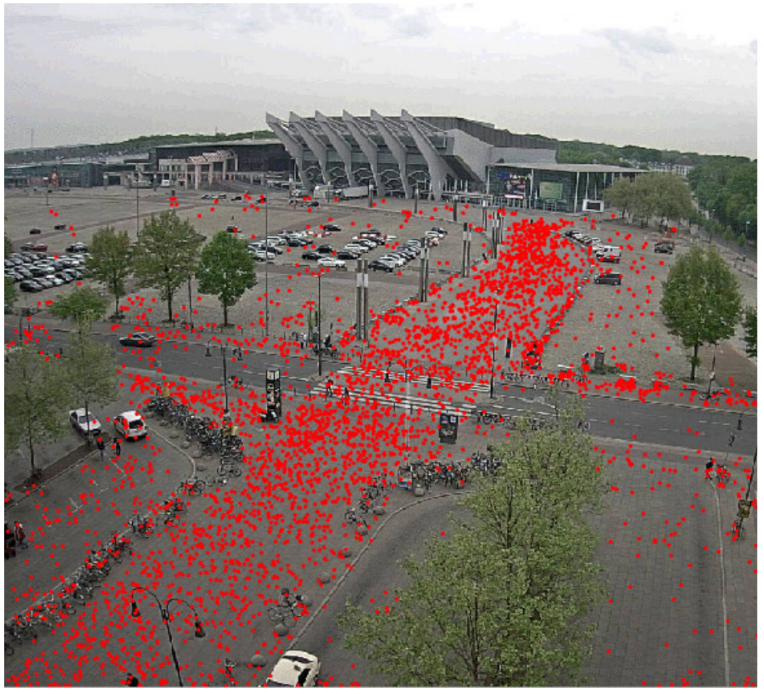
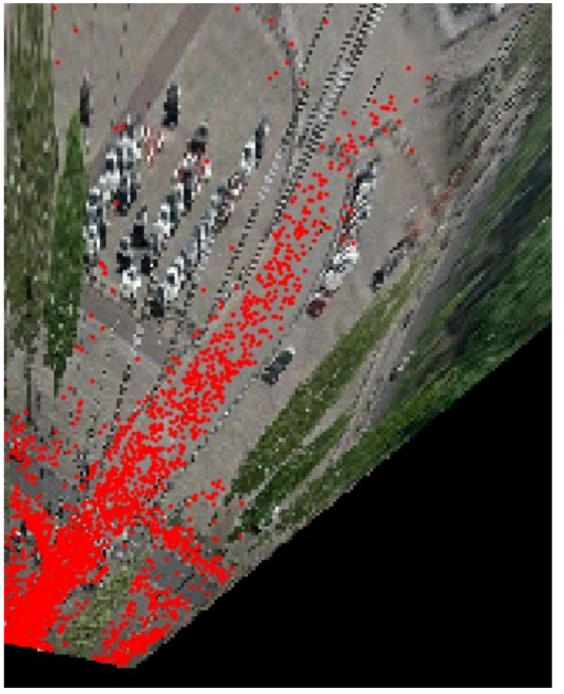
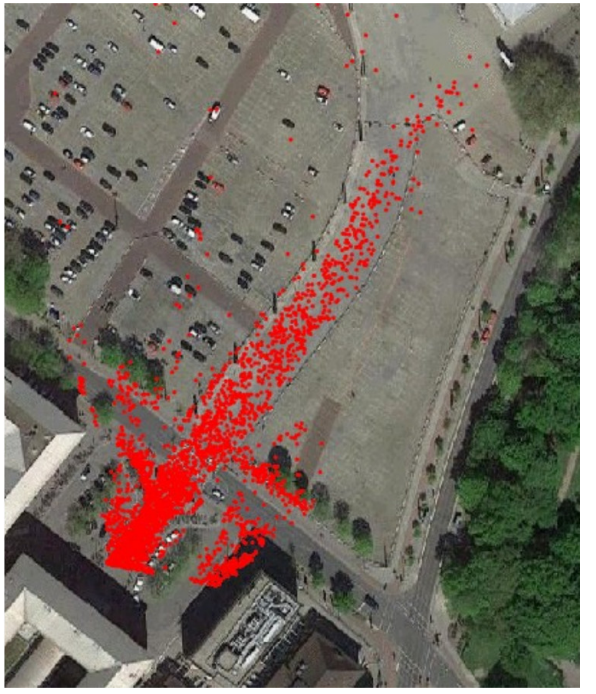
- distances in the image represent varying distances in reality
- we can't integrate other geospatial datasets (streets, POIs) or information from other webcams



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

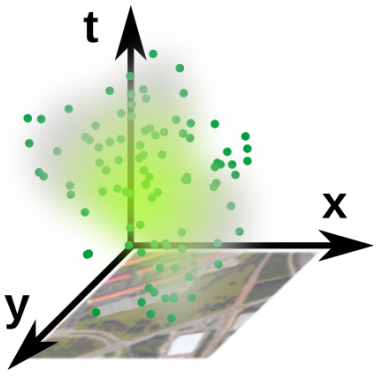


Georeferencing: example

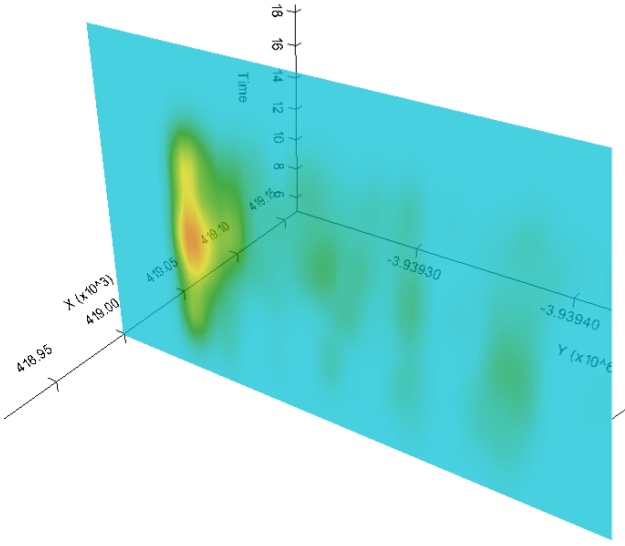
Caveats: some webcams change orientation, many objects such as benches, traffic marking are unsuitable as GCPs, stable objects such as statues can move too

STC visualization

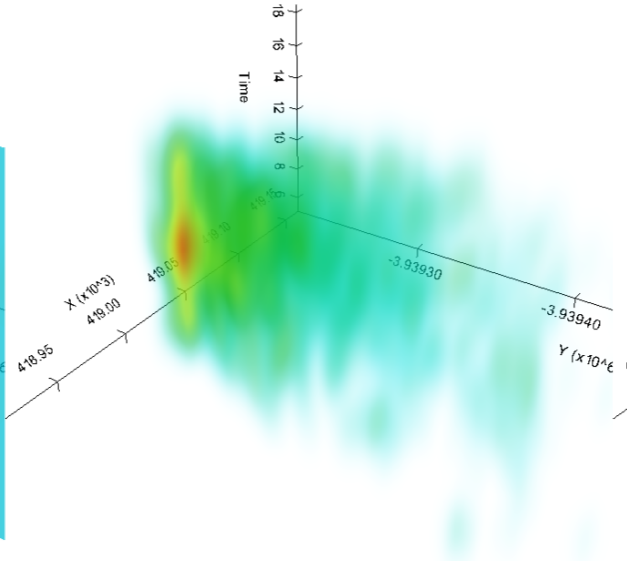


Space-time density of pedestrians represented as a 3D volume, computed using multivariate Kernel Density Estimation (KDE) with different spatial and temporal bandwidths

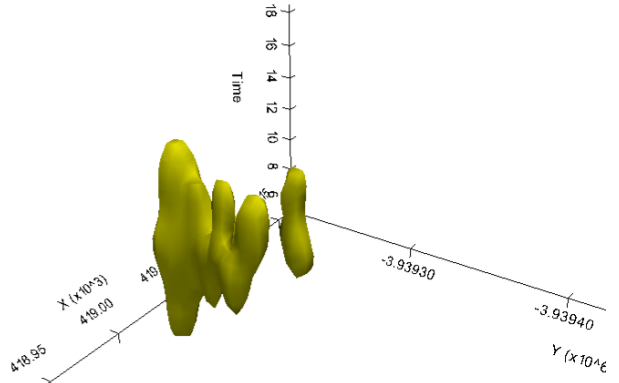
slice



volume rendering

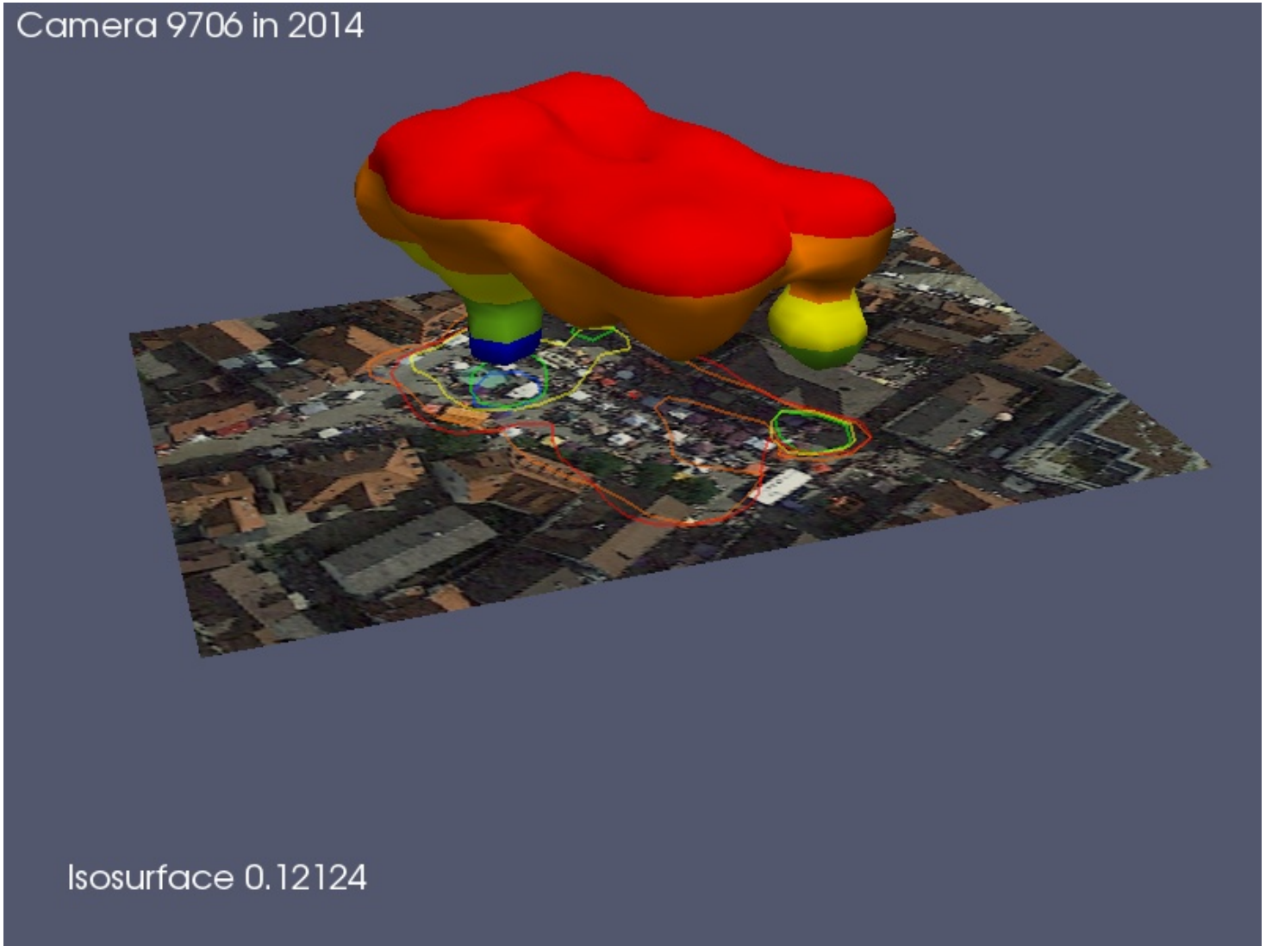


isosurface



Pedestrian density visualization

webcam 9706 (July), Ehingen, Germany



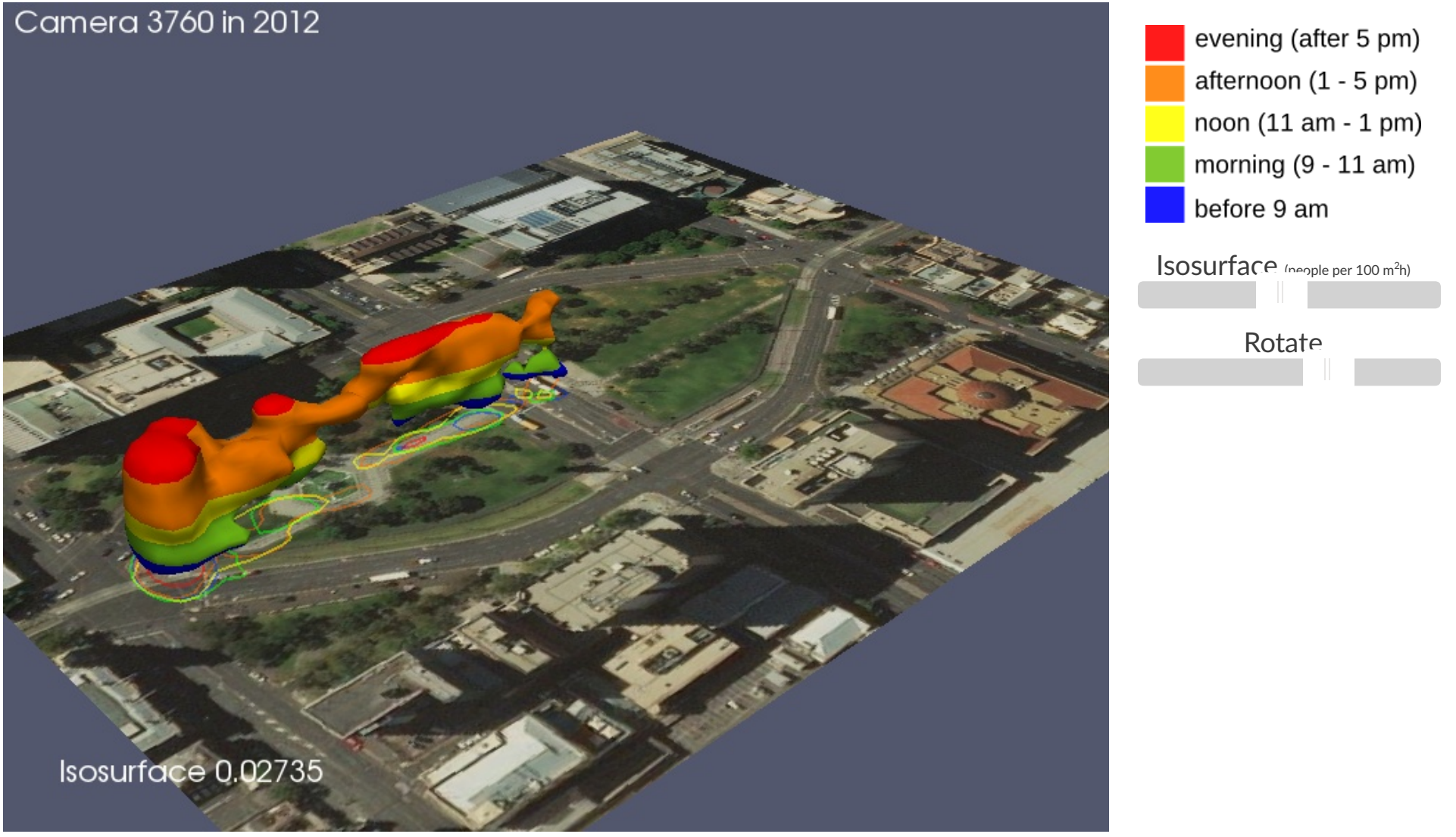
evening (after 5 pm)
afternoon (1 - 5 pm)
noon (11 am - 1 pm)
morning (9 - 11 am)
before 9 am

Isosurface (people per 100 m^2h)

Rotate

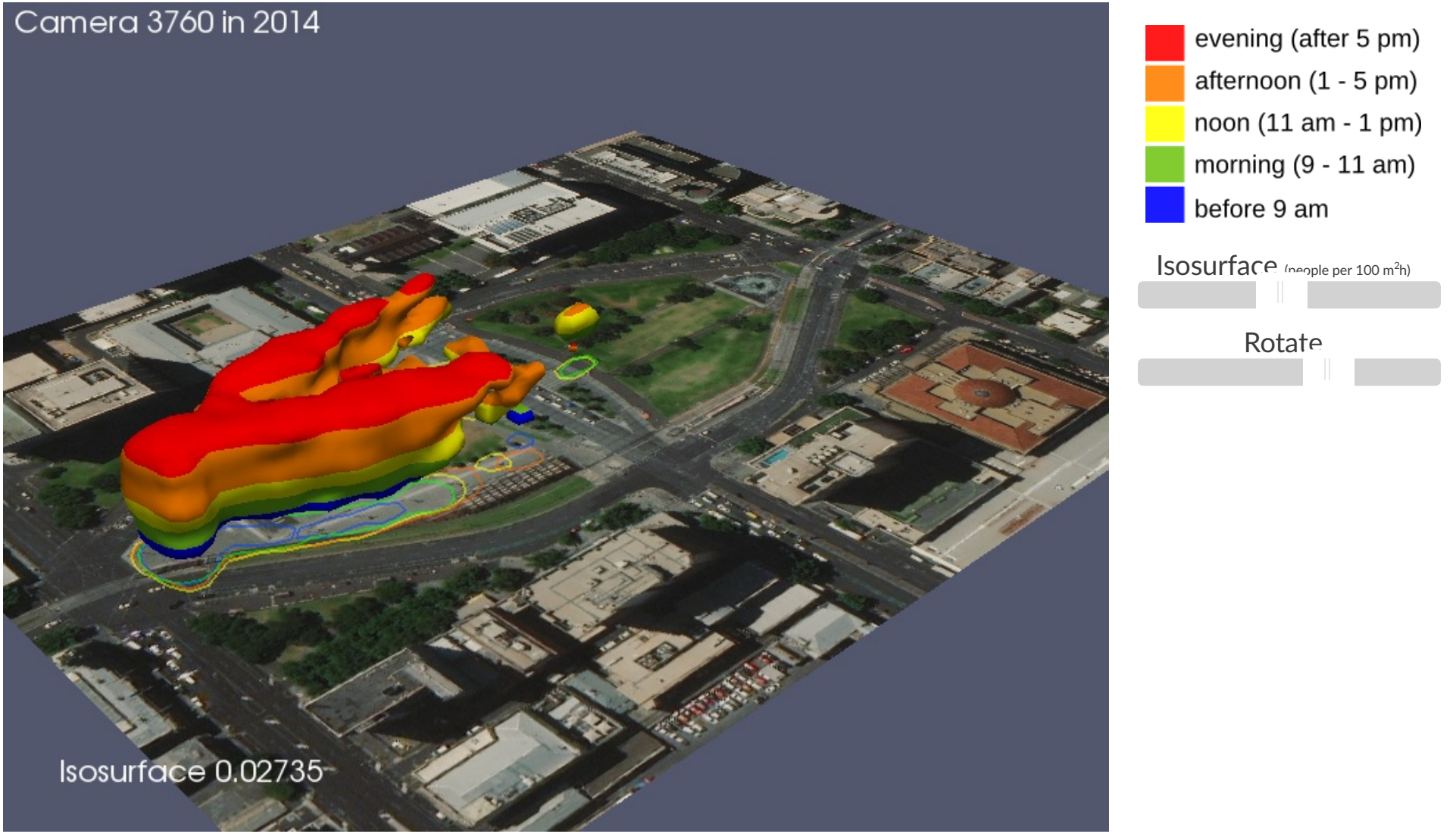
Effects of plaza reconstruction

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



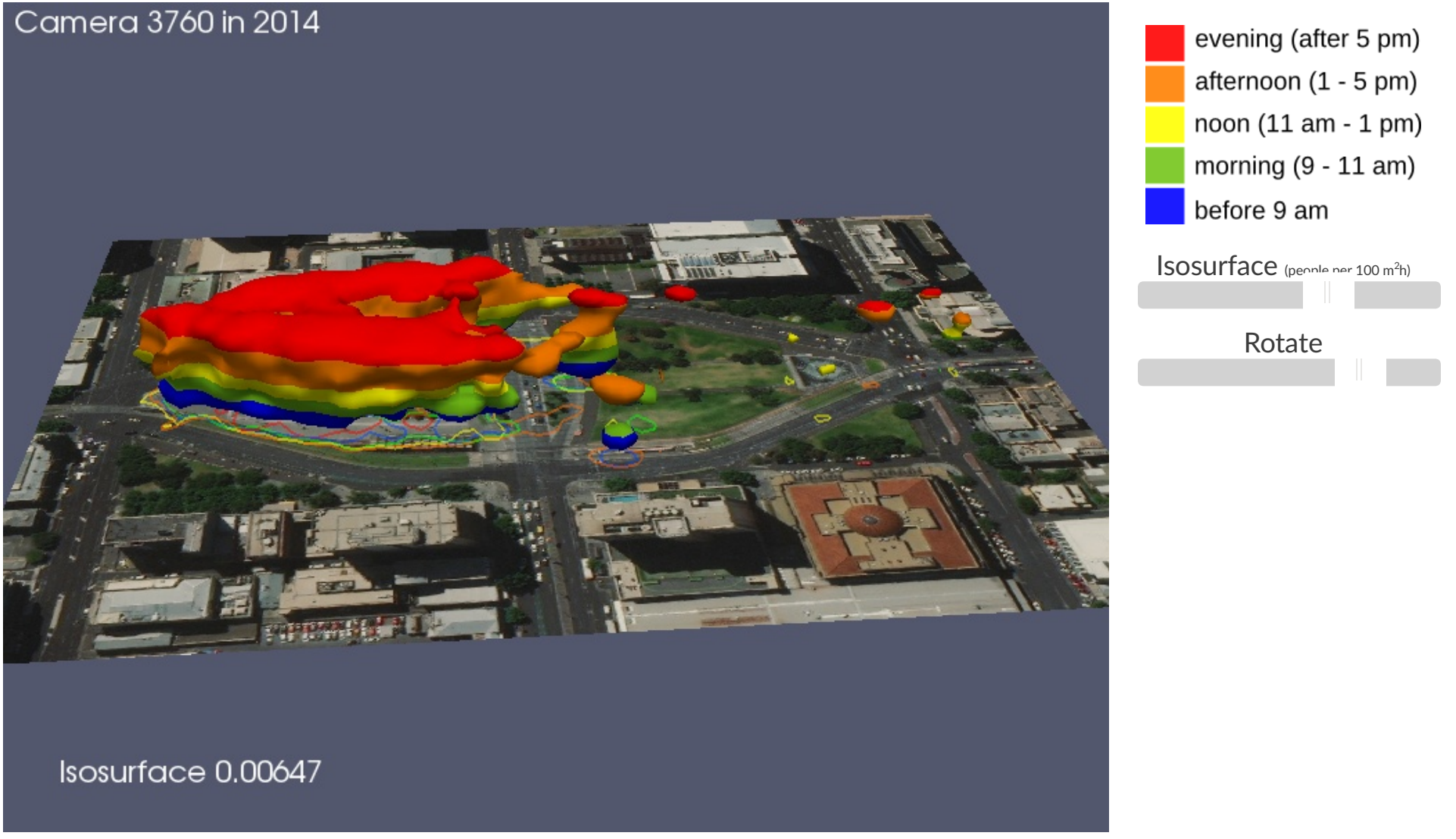
Effects of plaza reconstruction

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



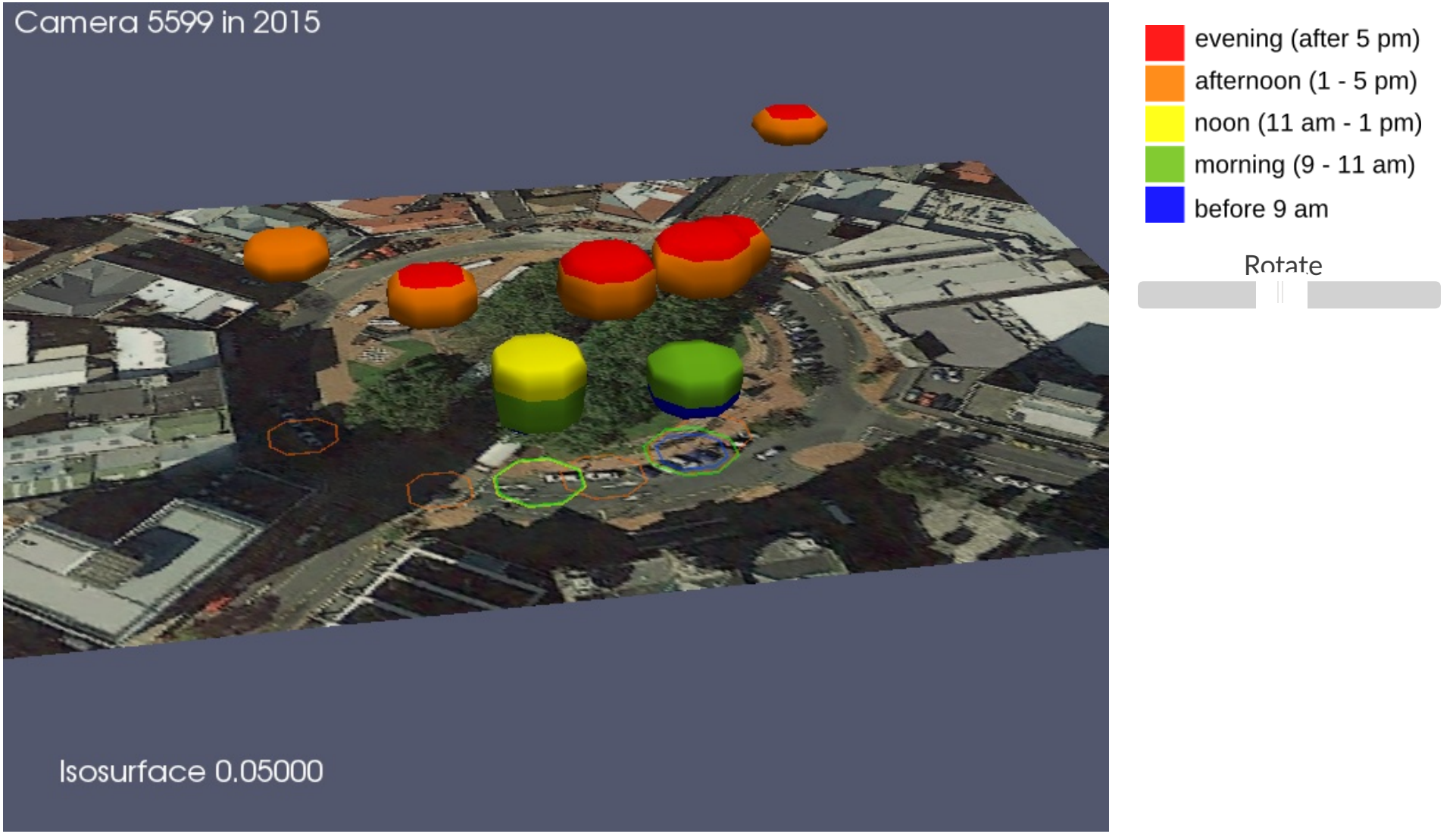
Change in pedestrian density (2014 minus 2012)

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



High density of pedestrians and vehicles (webcam 5599)

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

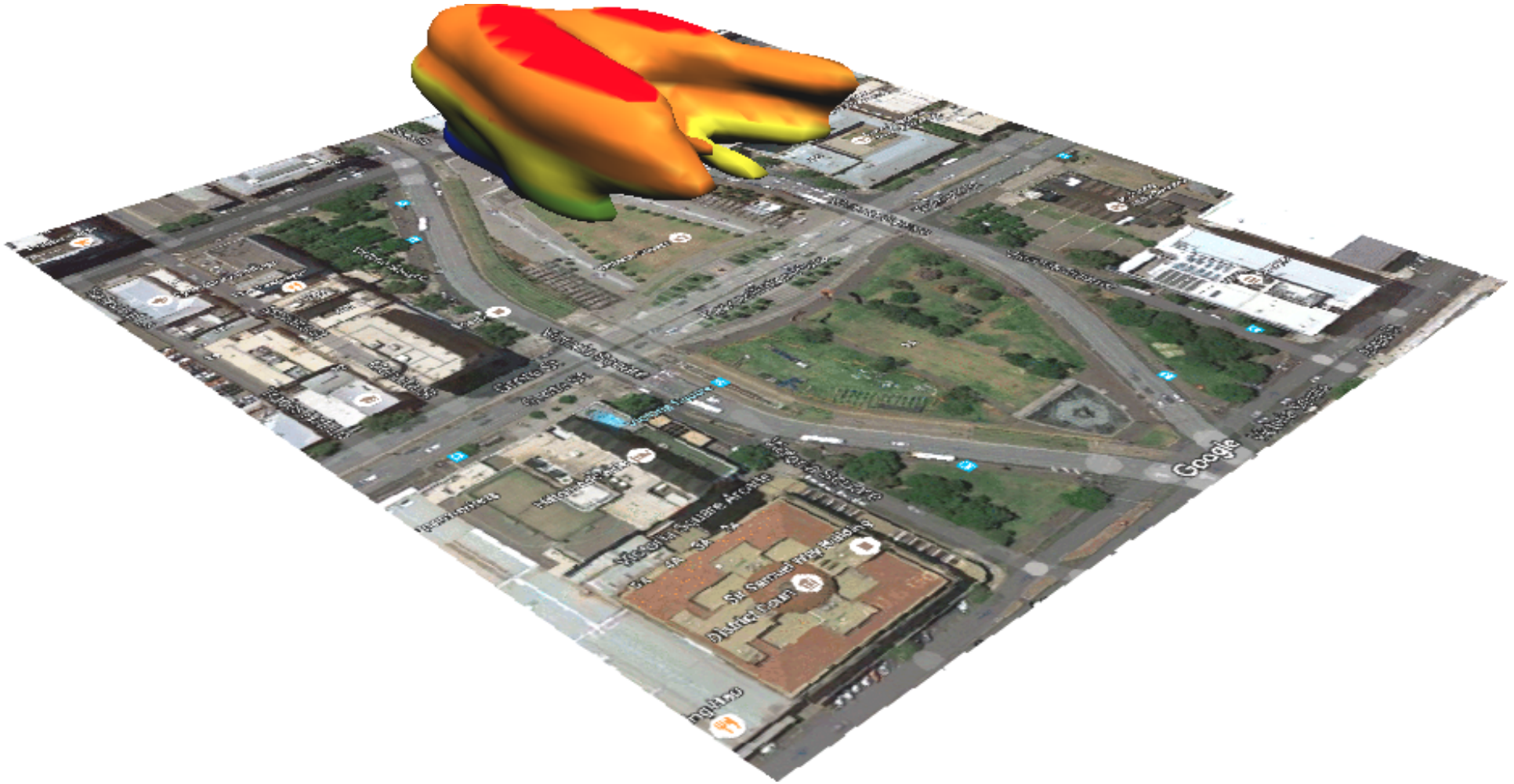


Software

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

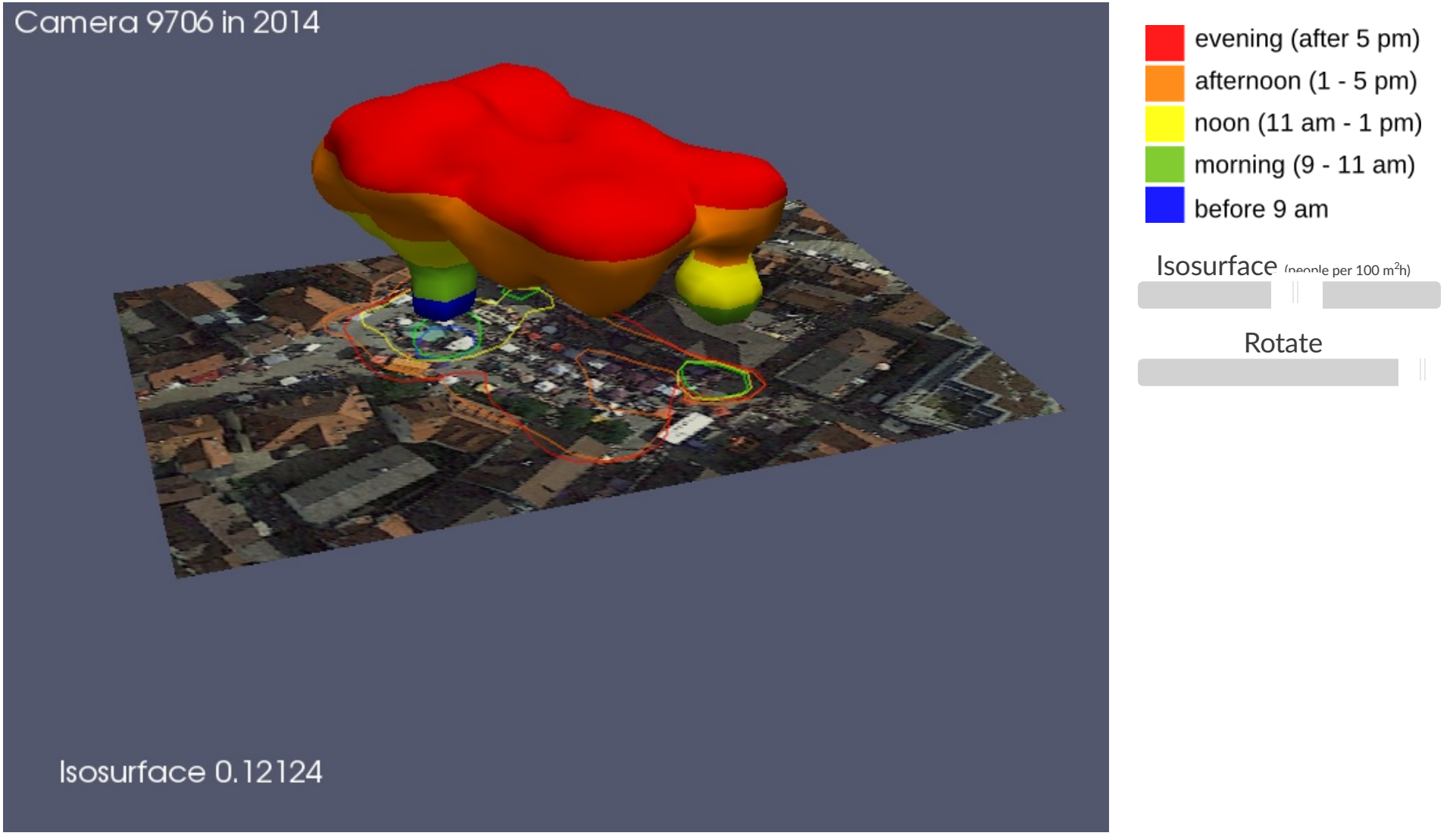
github.com/petrasovaa/amos-visualization

Visualization: GRASS GIS

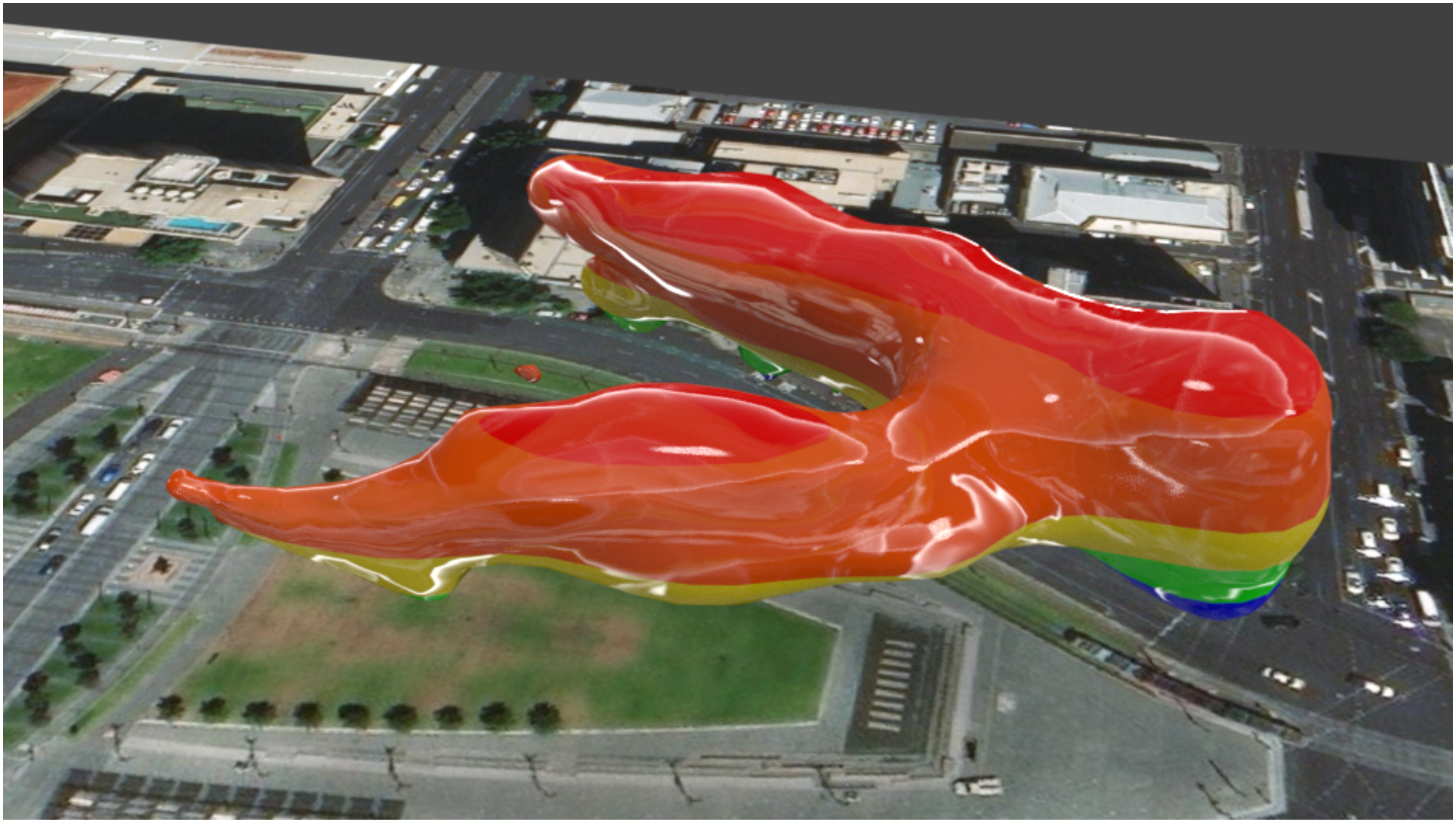


Visualization: ParaView

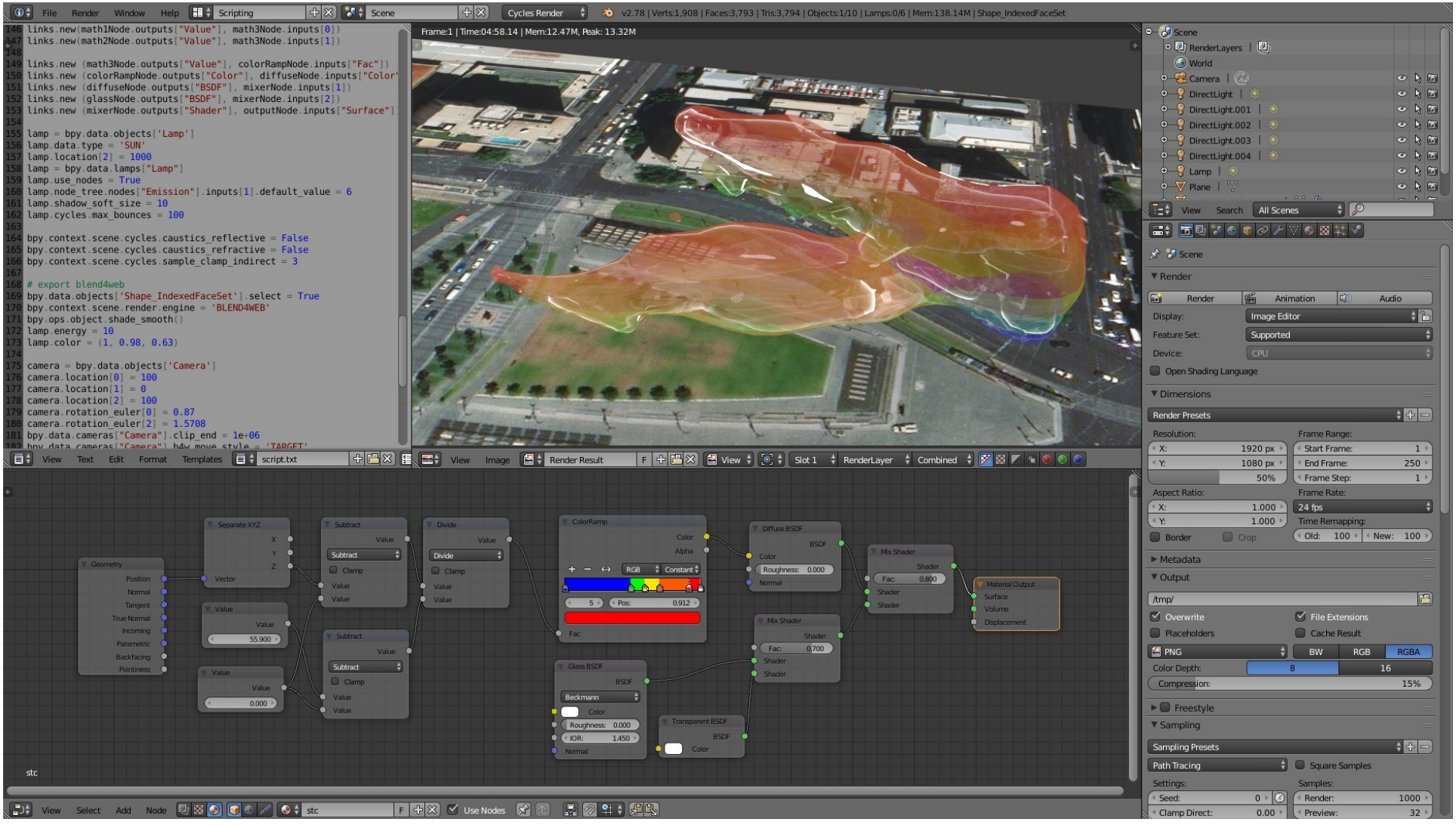
webcam 9706 (July), Ehingen, Germany



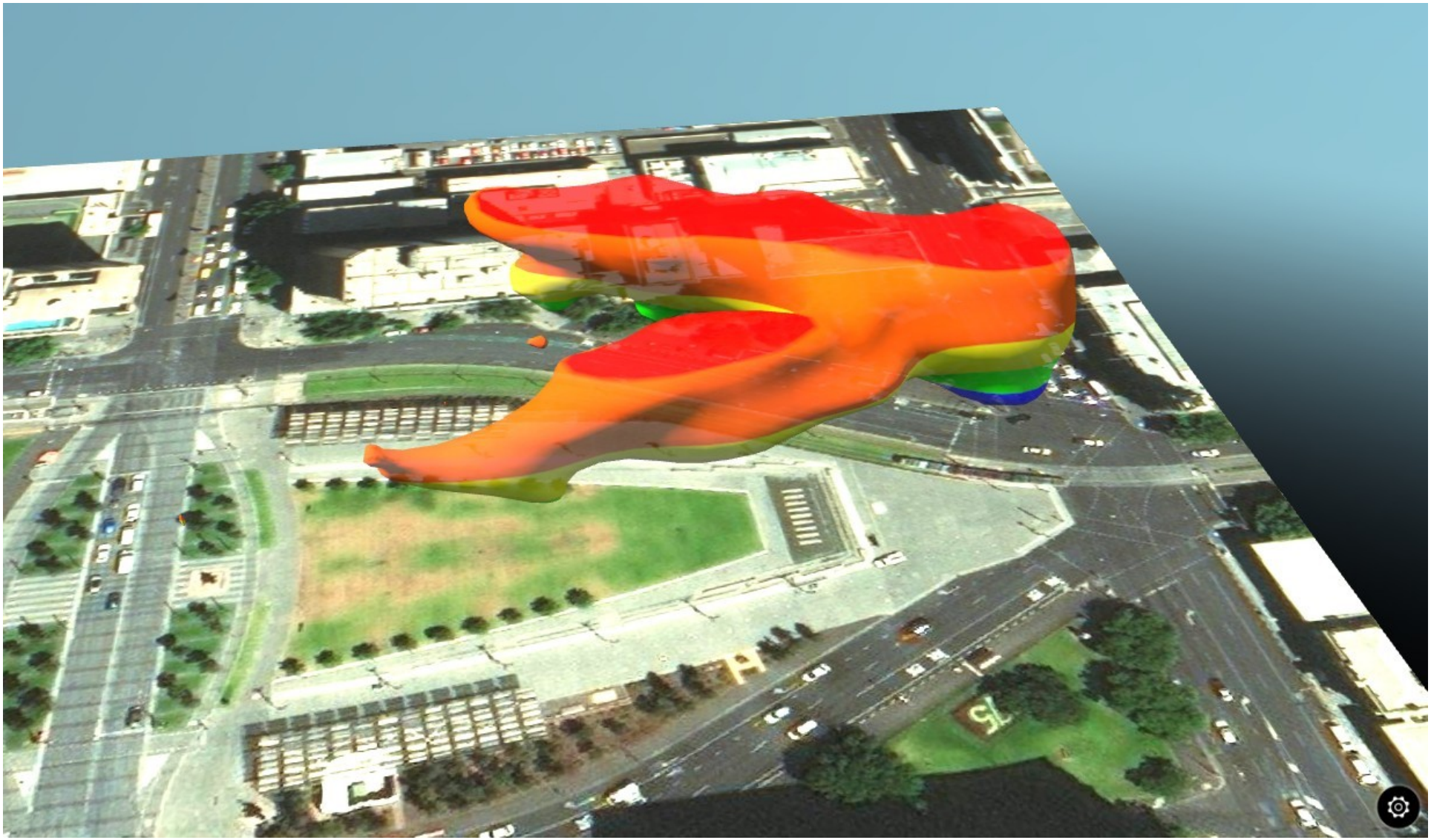
Visualization: Blender



Blender


File Render Window Help Scripting Scene Cycles Render v2.78 | Verts:1,908 | Faces:3,793 | Tris:3,794 | Objects:1/10 | Lamps:0/6 | Mem:138.14M | Shape_IndexedFaceSet
links.new(math1Node.outputs["Value"], math3Node.inputs[0])
links.new(math2Node.outputs["Value"], math3Node.inputs[1])
links.new (math3Node.outputs["Value"], colorRampNode.inputs["Fac"])
links.new (colorRampNode.outputs["Color"], diffuseNode.inputs["Color"
links.new (diffuseNode.outputs["BSDF"], mixerNode.inputs[1])
links.new (glassNode.outputs["BSDF"], mixerNode.inputs[2])
links.new (mixerNode.outputs["Shader"], outputNode.inputs["Surface"]
lamp = bpy.data.objects['Lamp']
lamp.data.type = 'SUN'
lamp.location[2] = 1000
lamp = bpy.data.lamps["Lamp"]
lamp.use_nodes = True
lamp.node_tree.nodes["Emission"].inputs[1].default_value = 6
lamp.shadow_soft_size = 10
lamp.cycles.max_bounces = 100
bpy.context.scene.cycles.caustics_reflective = False
bpy.context.scene.cycles.caustics_refractive = False
bpy.context.scene.cycles.sample_clamp_indirect = 3
# export blend4web
bpy.data.objects['Shape_IndexedFaceSet'].select = True
bpy.context.scene.render.engine = 'BLEND4WEB'
bpy.ops.object.shade_smooth()
lamp.energy = 10
lamp.color = (1, 0.98, 0.63)
camera = bpy.data.objects['Camera']
camera.location[0] = 100
camera.location[1] = 0
camera.location[2] = 100
camera.rotation_euler[0] = 0.87
camera.rotation_euler[2] = 1.5708
bpy.data.cameras["Camera"].clip_end = 1e+06
Frame:1 | Time:04:58.14 | Mem:12.47M, Peak: 13.32M
Scene
RenderLayers
World
Camera
DirectLight
DirectLight.001
DirectLight.002
DirectLight.003
DirectLight.004
Lamp
Plane
View Search All Scenes
Render
Render Animation Audio
Display: Image Editor
Feature Set: Supported
Device: CPU
Open Shading Language
Dimensions
Render Presets
Resolution:
X: 1920 px
Y: 1080 px
50%
Frame Range:
Start Frame: 1
End Frame: 250
Frame Step: 1
Aspect Ratio:
X: 1.000
Y: 1.000
Frame Rate:
24 fps
Time Remapping:
Old: 100 New: 100
Border Crop
Metadata
Output
/tmp/
Overwrite File Extensions
Placeholders Cache Result
PNG BW RGB RGBA
Color Depth: 8 16
Compression: 15%
Freestyle
Sampling
Sampling Presets
Path Tracing Square Samples
Settings:
Seed: 0
Clamp Direct: 0.00
Samples:
Render: 1000
Preview: 32
View Text Edit Format Templates script.txt
View Image Render Result View Slot 1 RenderLayer Combined
Geometry
Separate XYZ
Subtract
Divide
ColorRamp
Diffuse BSDF
Mix Shader
Material Output
Value
Glass BSDF
Transparent BSDF
stc
View Select Add Node stc Use Nodes

Visualization: Blend4Web



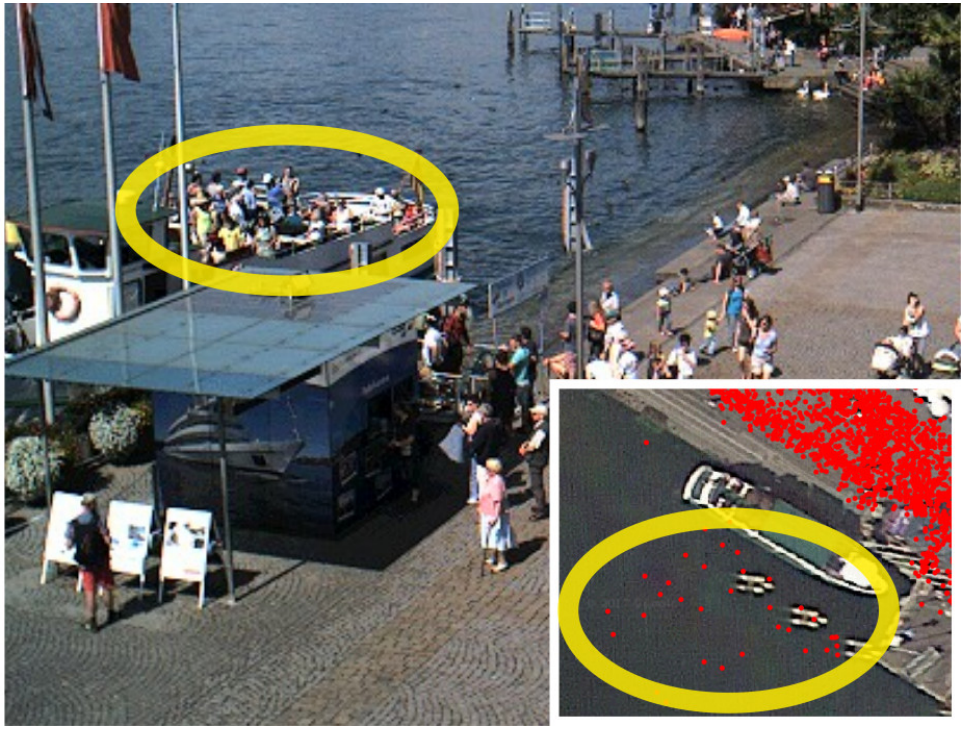
Conclusion & Future work

- 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

Appendix

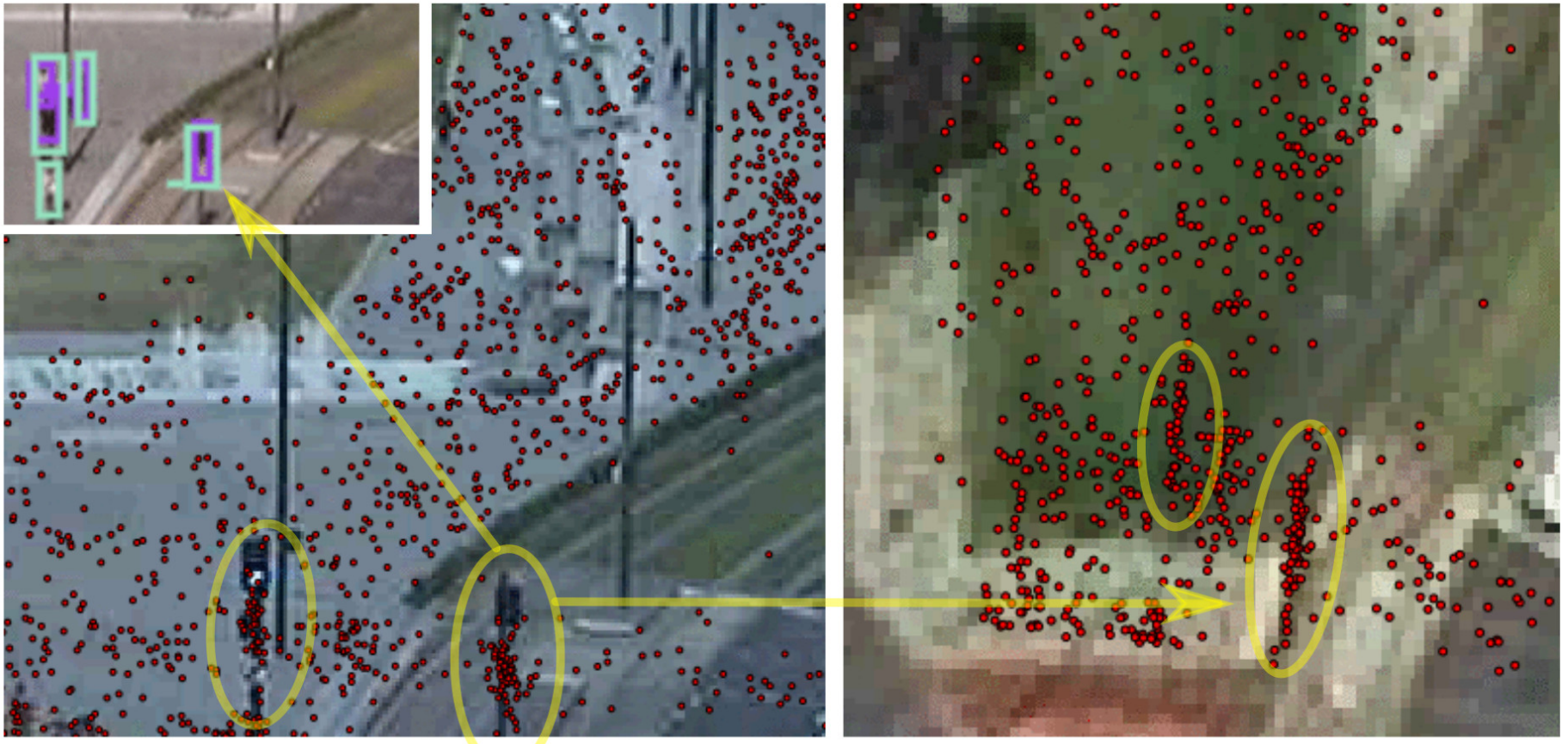
Challenges: webcam geometry and view

- 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

References:

- Hipp, J. A., Adlakha, D., Gernes, R., Kargol, A., Pless, R., Drive, O. B., Louis, S. (2013). Do You See What I See: Crowdsource Annotation of Captured Scenes, 24–25. http://doi.org/10.1145/2526667.2526671
- Hipp, J. A., Manteiga, A., Burgess, A., Stylianou, A., Pless, R. (2016). Webcams, Crowdsourcing, and Enhanced Crosswalks: Developing a Novel Method to Analyze Active Transportation. Front. Public Health, 4(97). http://doi.org/10.3389/fpubh.2016.00097
- Jacobs, N., Roman, N., Pless, R. (2007). Consistent temporal variations in many outdoor scenes. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition. http://doi.org/10.1109/CVPR.2007.383258