ETH zürich

SmartAIR — IFD / SDSC

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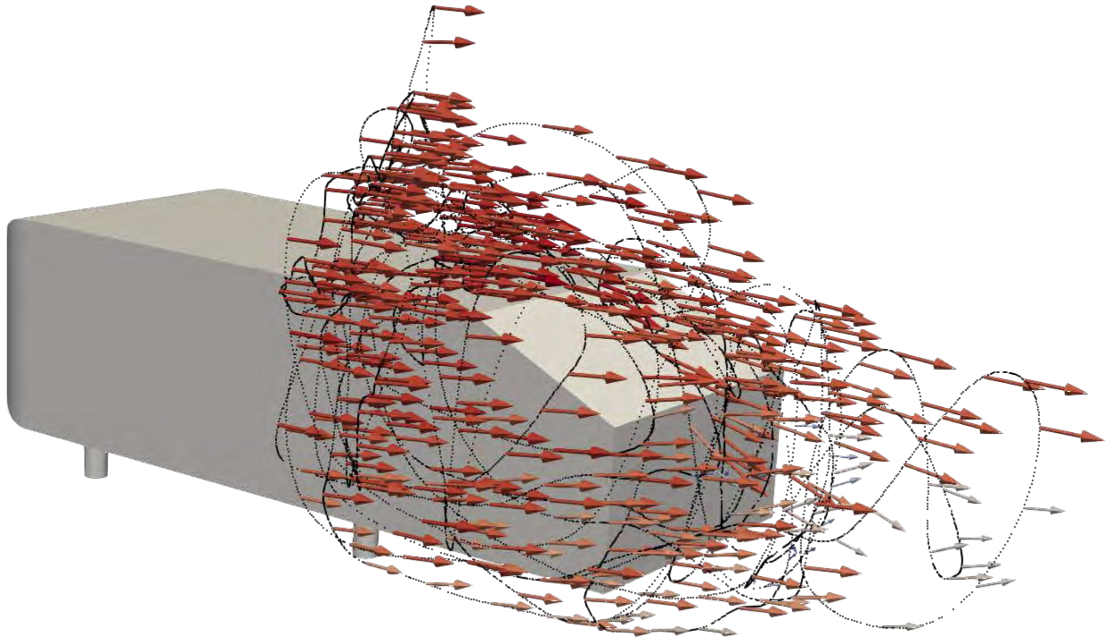
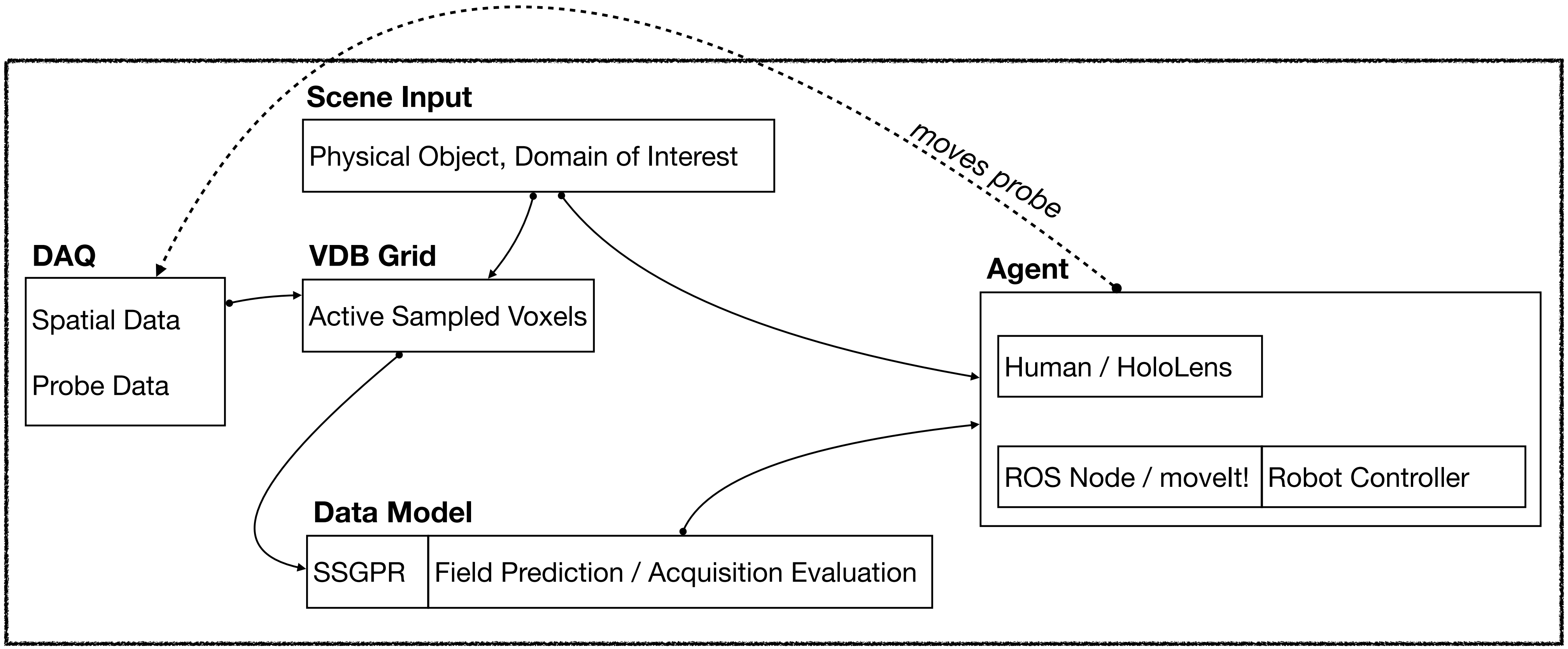
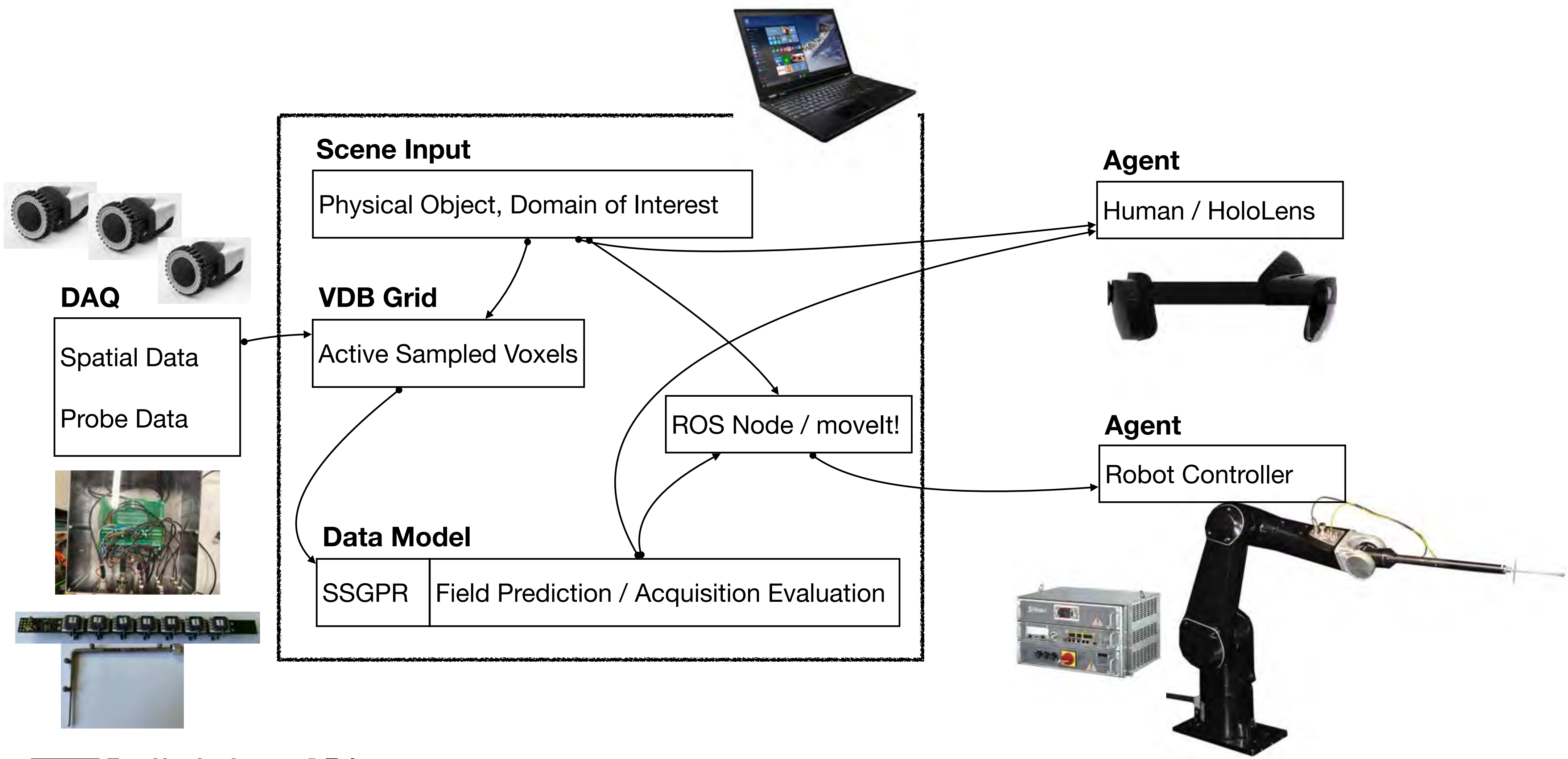
Outline

I. **Current State of System**

II. **Available Data Sets**




moves probe
Scene Input
Physical Object, Domain of Interest
DAQ
Spatial Data
Probe Data
VDB Grid
Active Sampled Voxels
Agent
Human / HoloLens
ROS Node / moveIt!
Robot Controller
Data Model
SSGPR
Field Prediction / Acquisition Evaluation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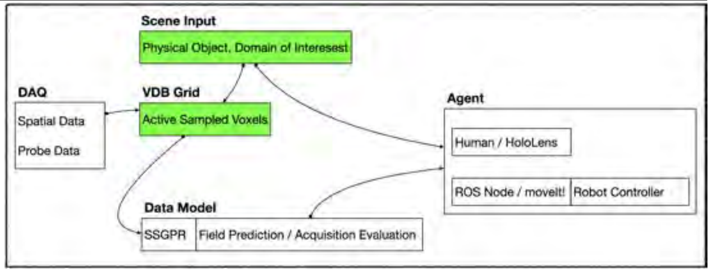
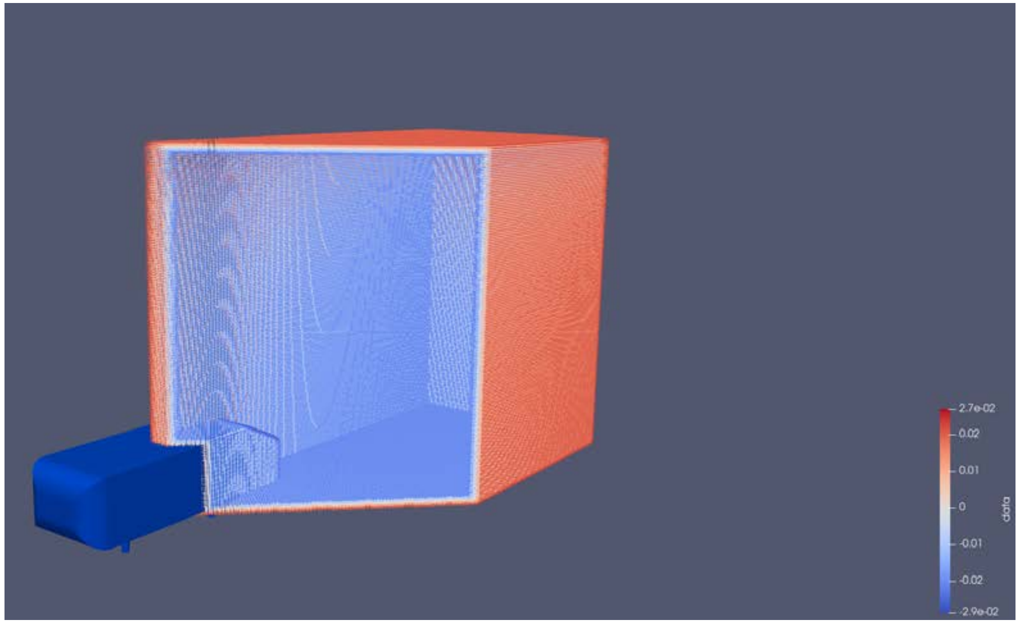
Scene Input & VDB Grid

CAD files describing scene and domain of interest as input.

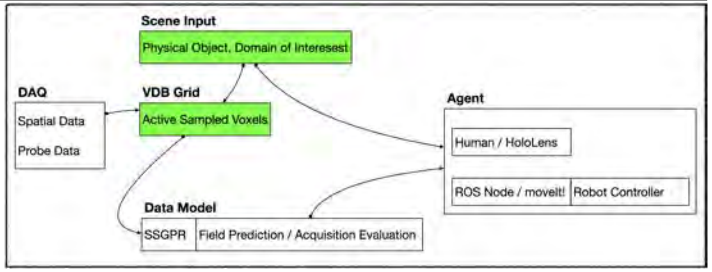
CSG operation creating B+ tree (openvdb.org) of investigated volume.

Sampled data sparse, prediction of field dense.





Cut through signed distance field of investigated volume



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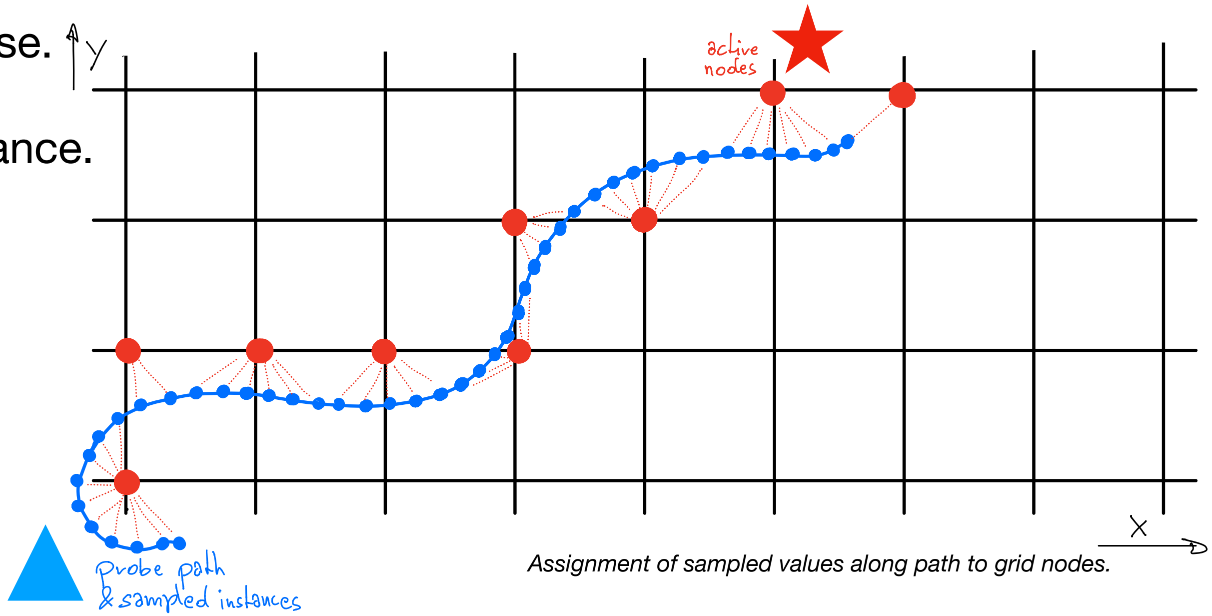
Welford's online algorithm for mean and variance.

Smoothing of data for further processing.



Assignment of sampled values along path to grid nodes.

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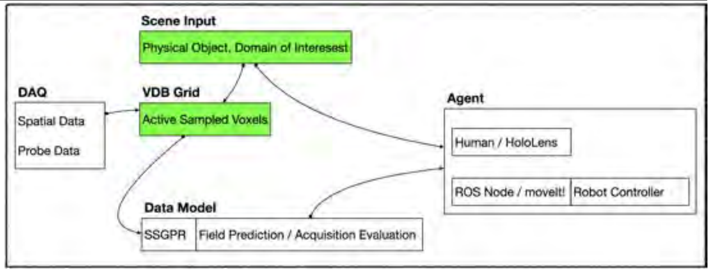

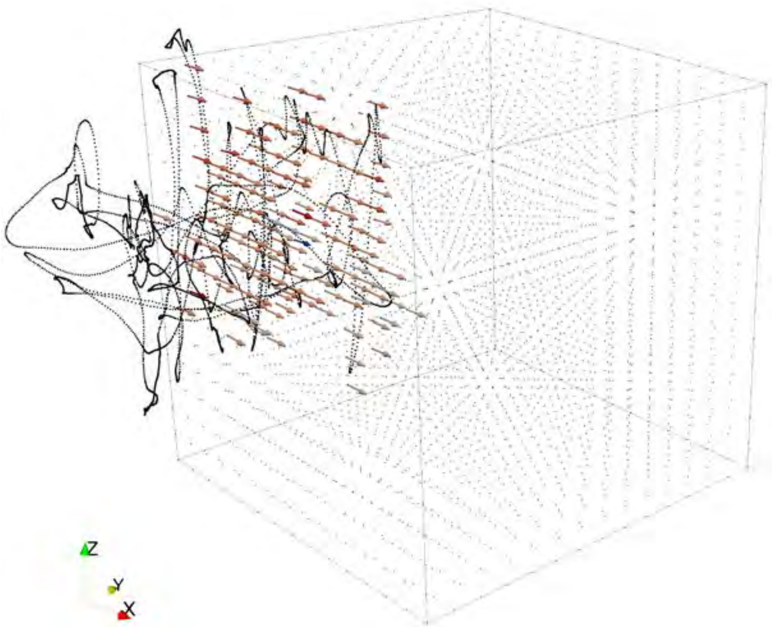

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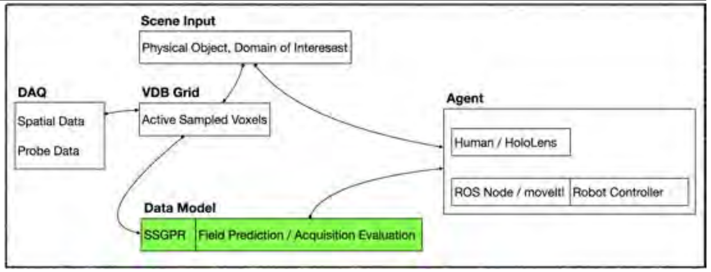

Data Model

Model field properties:

- pressure (scalar field)
- velocity (vector field)

Gaussian Process Regression / Kriging with anisotropic Radial Basis Function (RBF) kernel.

Limitations with fast updates (streaming data) and large data sets. Cubic time complexity $\mathcal{O}(N^3)$ due to matrix inversion.

$$\mathbf{A}\mathbf{w} = \mathbf{y} \tag{1}$$

$$\mathbf{A} = \mathbf{K}\left(\mathbf{X},\mathbf{X}\right) + \sigma_n^2\mathbf{I} \tag{2}$$

$$K_{ij} = k(\mathbf{x}_i,\mathbf{x}_j) = \sigma_F^2\ e^{\left(-\frac{1}{2}(\mathbf{x}_i-\mathbf{x}_j)^T\mathbf{M}(\mathbf{x}_i-\mathbf{x}_j)\right)} \tag{3}$$

$$\mathbf{R} = cholesky\left(\mathbf{A}\right) \tag{4}$$

$$\mathbf{w} = \mathbf{R} \setminus \left(\mathbf{R}^T \setminus \mathbf{y}\right) \tag{5}$$

$$\mathbf{v} = \mathbf{R}^T \setminus \mathbf{k}\left(\mathbf{X},\mathbf{x}\right) \tag{6}$$

$$\mu(\mathbf{x}^*) = \mathbf{k}\left(\mathbf{x}^*,\mathbf{X}\right)\ \mathbf{w} \tag{7}$$

$$\sigma^2(\mathbf{x}^*) = k\left(\mathbf{x}^*,\mathbf{x}^*\right) - \mathbf{v}^T\mathbf{v} \tag{8}$$

Rasmussen, C. E. & Williams, C. K. I. (2006) *Gaussian processes for machine learning* . Cambridge, Mass: MIT Press.

Data Model

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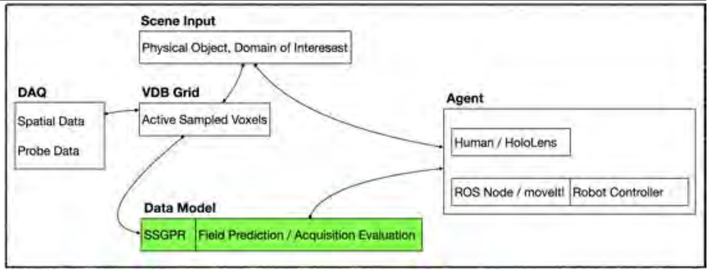
- velocity (vector field)

Sparse Spectrum Gaussian Process Regression (SSGPR).

Approximation of RBF kernel with trigonometric basis functions => covariance function with fixed size.



$$\mathbf{\Omega} \sim 1\mathcal{N}(\mathbf{0}, \mathbf{I}) \tag{9}$$

$$\phi(\mathbf{x}) = \frac{\sigma_f}{\sqrt{D}}\left[\sin(\mathbf{\Omega x})^T, \cos(\mathbf{\Omega x})^T\right]^T \tag{10}$$

$$\mathbf{\Phi} = [\phi(\mathbf{x}_1), \phi(\mathbf{x}_2), ..., \phi(\mathbf{x}_n)] \tag{11}$$

$$\mathbf{A} = \mathbf{\Phi}^T\mathbf{\Phi} + \sigma_n^2\mathbf{I} \tag{12}$$

$$\mathbf{b} = \mathbf{\Phi y} \tag{13}$$

$$\mu(\mathbf{x}^*) = \phi(\mathbf{x}^*)^T\, \mathbf{R} \setminus \left(\mathbf{R}^T \setminus \mathbf{b}\right) \tag{14}$$

$$\sigma^2(\mathbf{x}^*) = \sigma_n^2 + \sigma_n^2\, ||\mathbf{R} \setminus \phi(\mathbf{x}^*)||^2 \tag{15}$$

Lázaro-Gredilla, M., Quinonero-Candela, J., Rasmussen, C.E. and Figueiras-Vidal, A.R., 2010. Sparse spectrum Gaussian process regression. *The Journal of Machine Learning Research*, *11*, pp.1865-1881.

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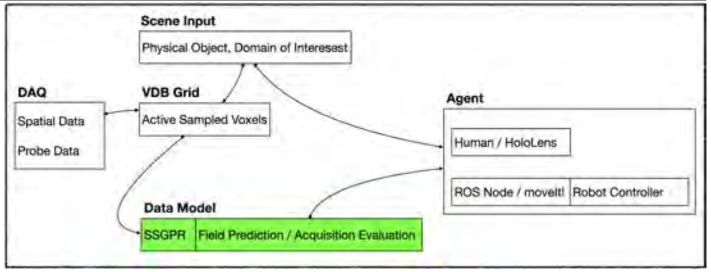
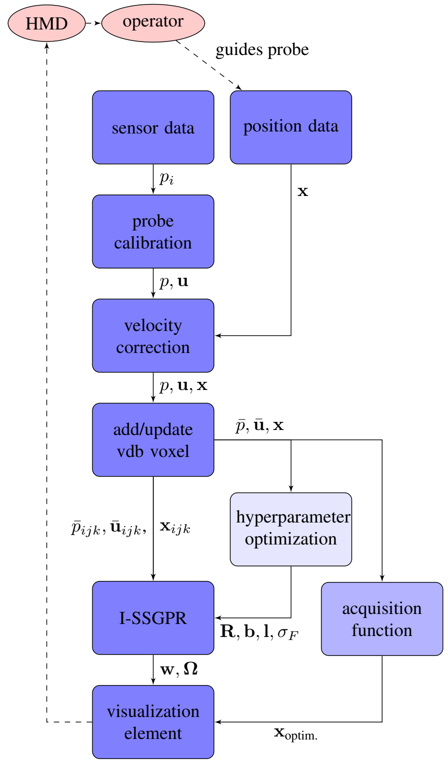
Sparse Spectrum Gaussian Process Regression

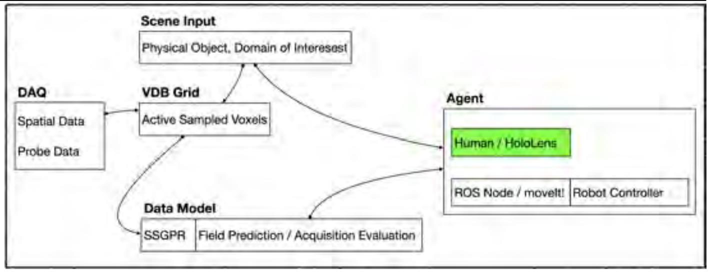
Periodically online optimization of sparse kernel Hyperparameters with neg. log. marginal likelihood. Combining SSGPR and Iterative-SSGPR allows for minimal prior knowledge. Implemented via PyTorch C++ Interface.

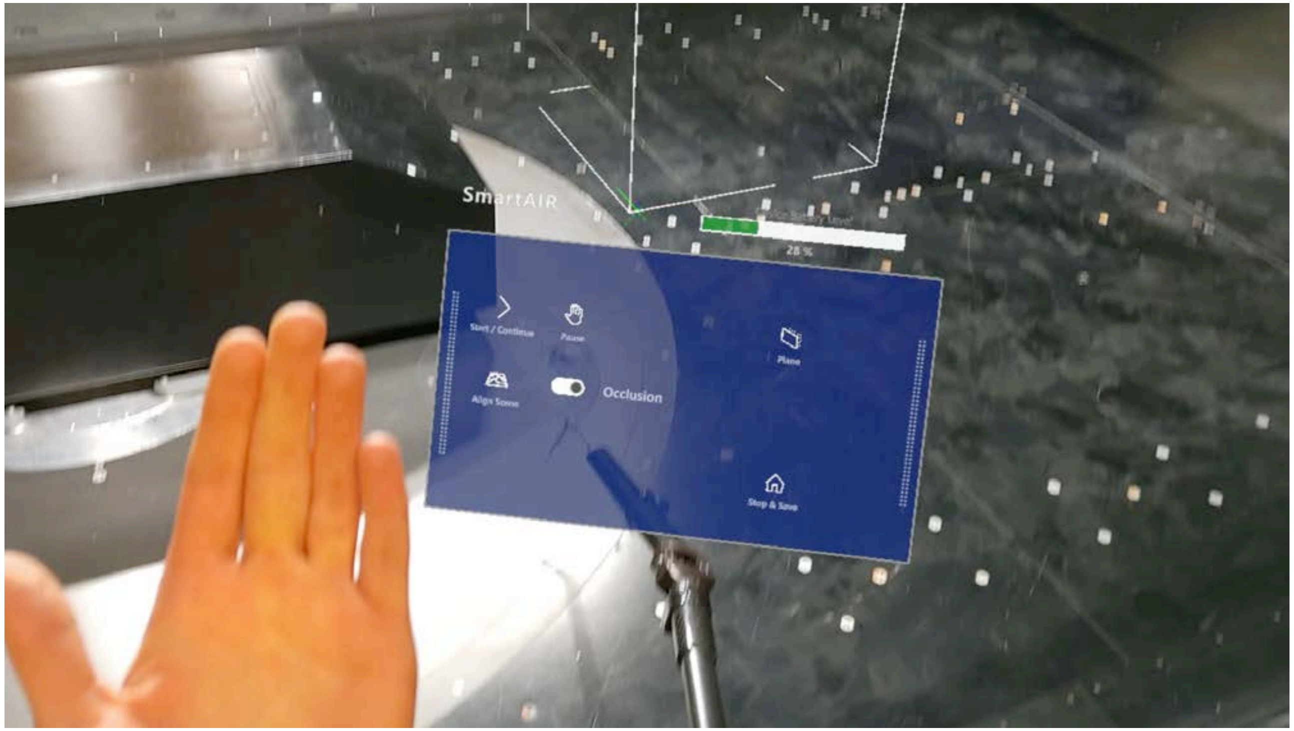
=> goal to still run on portable computer (Laptop)…





Human Agent / HoloLens





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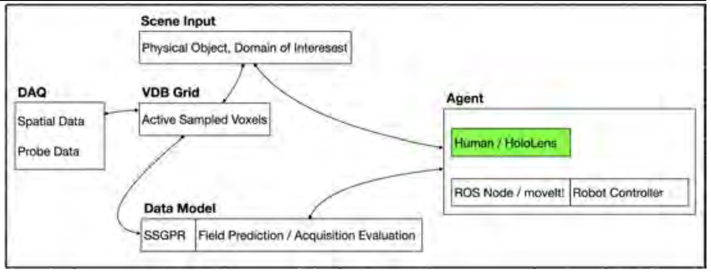
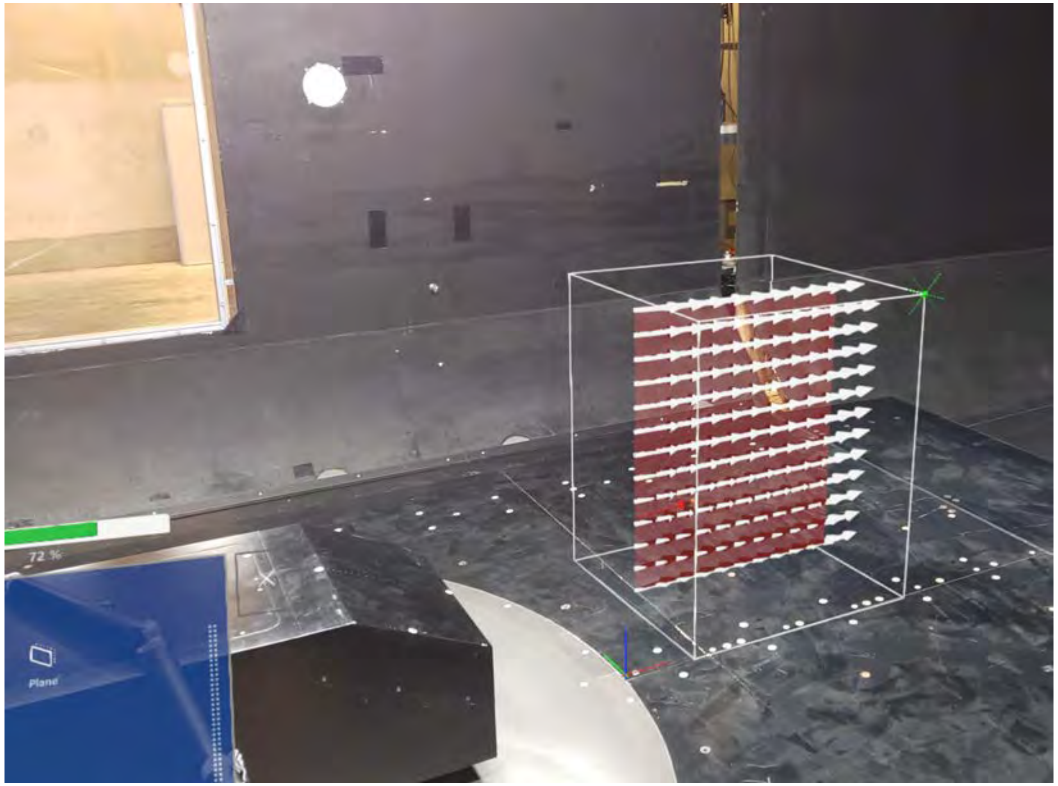
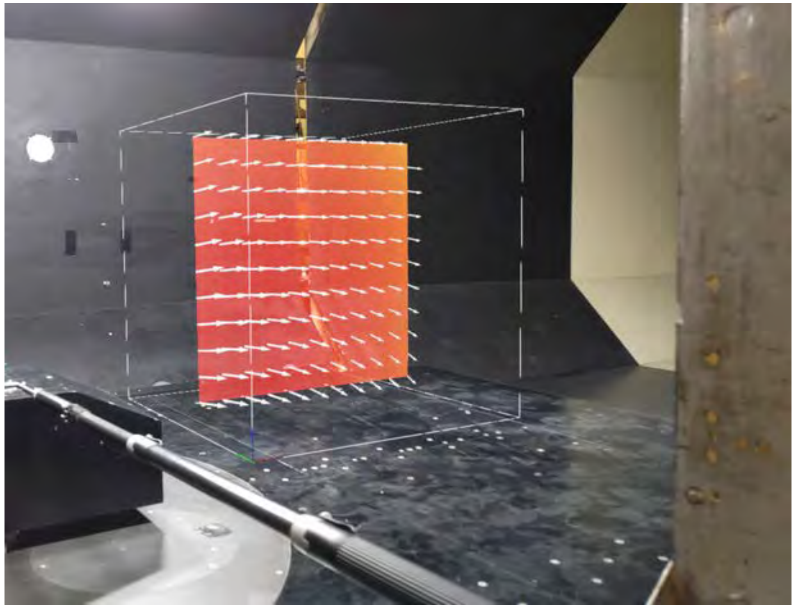
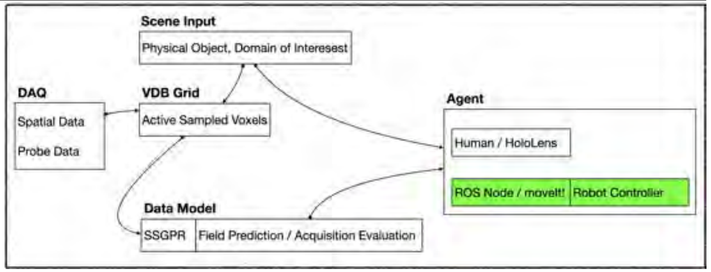
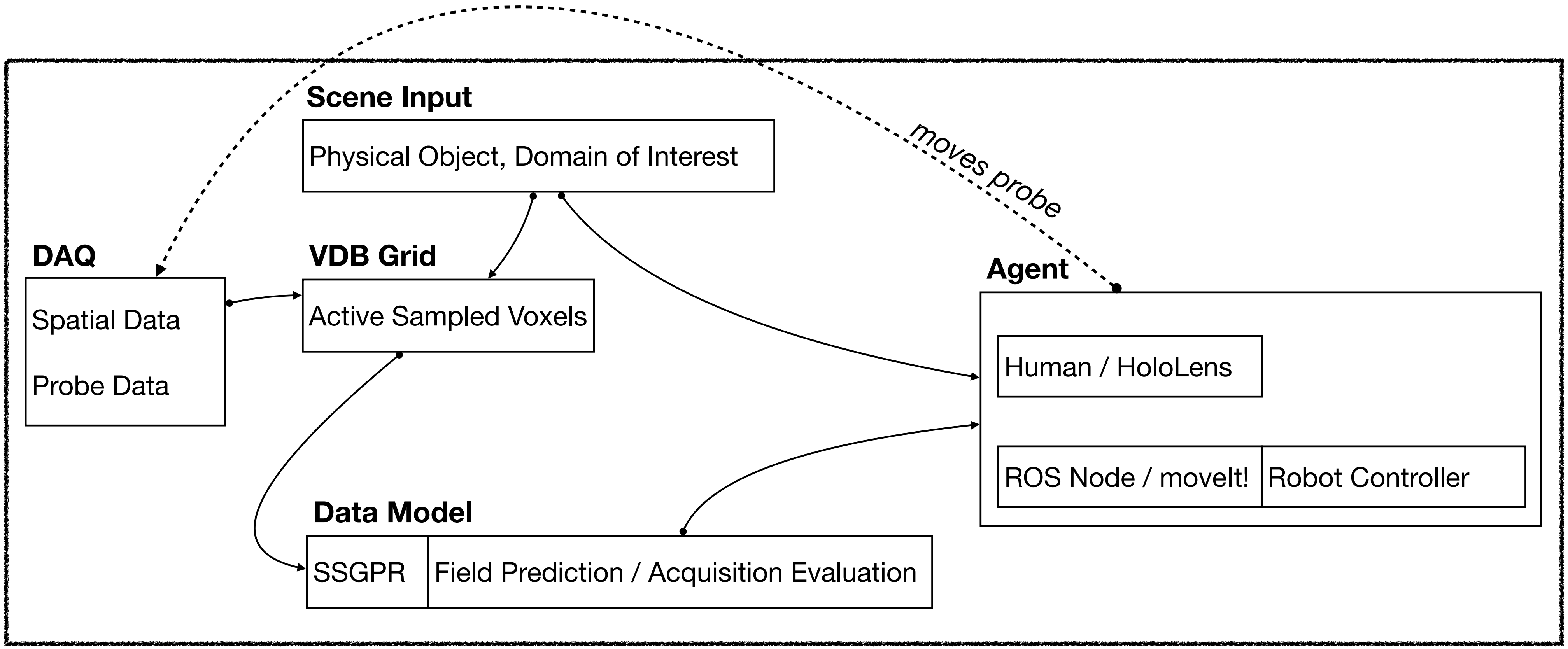






Robotic Agent

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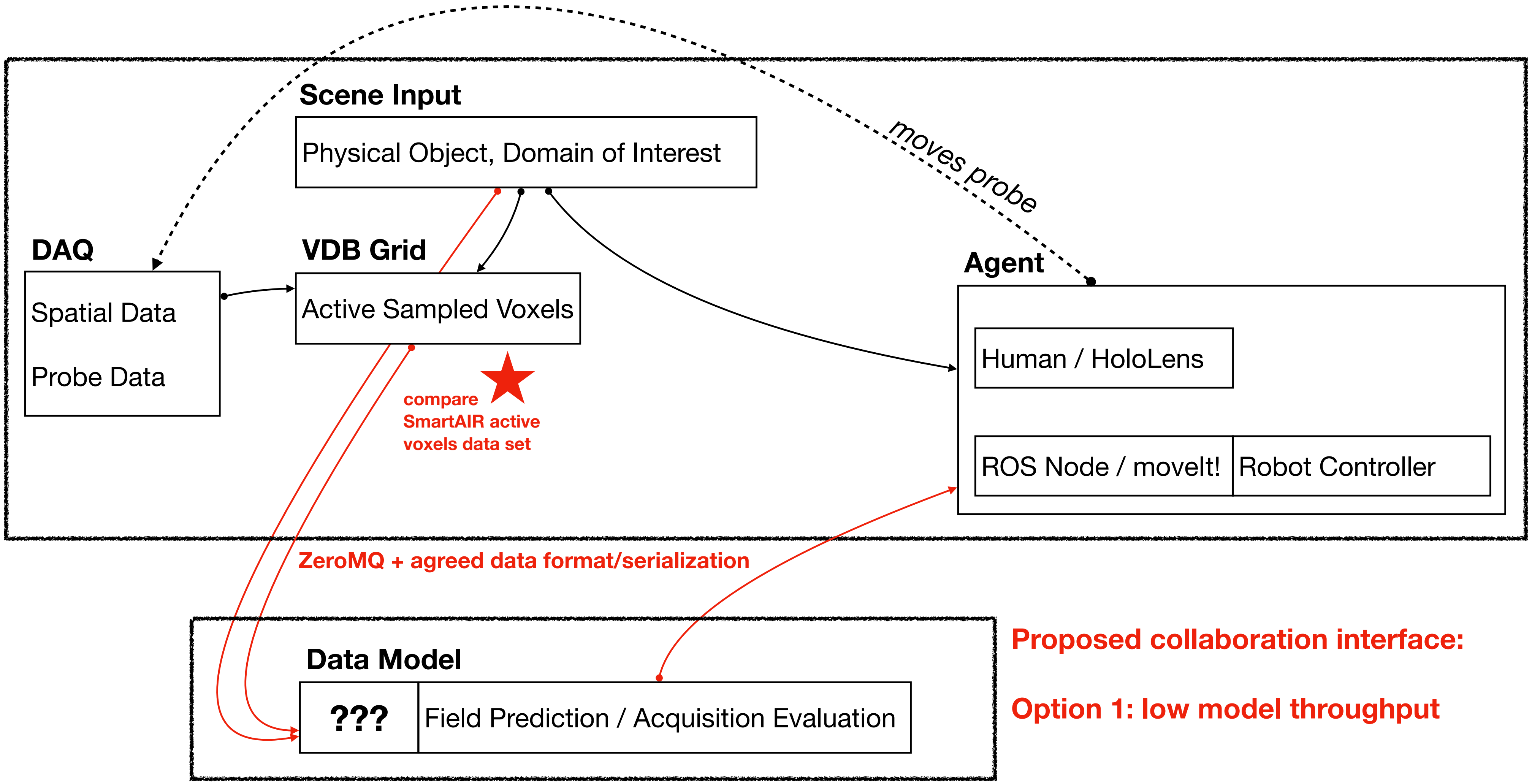
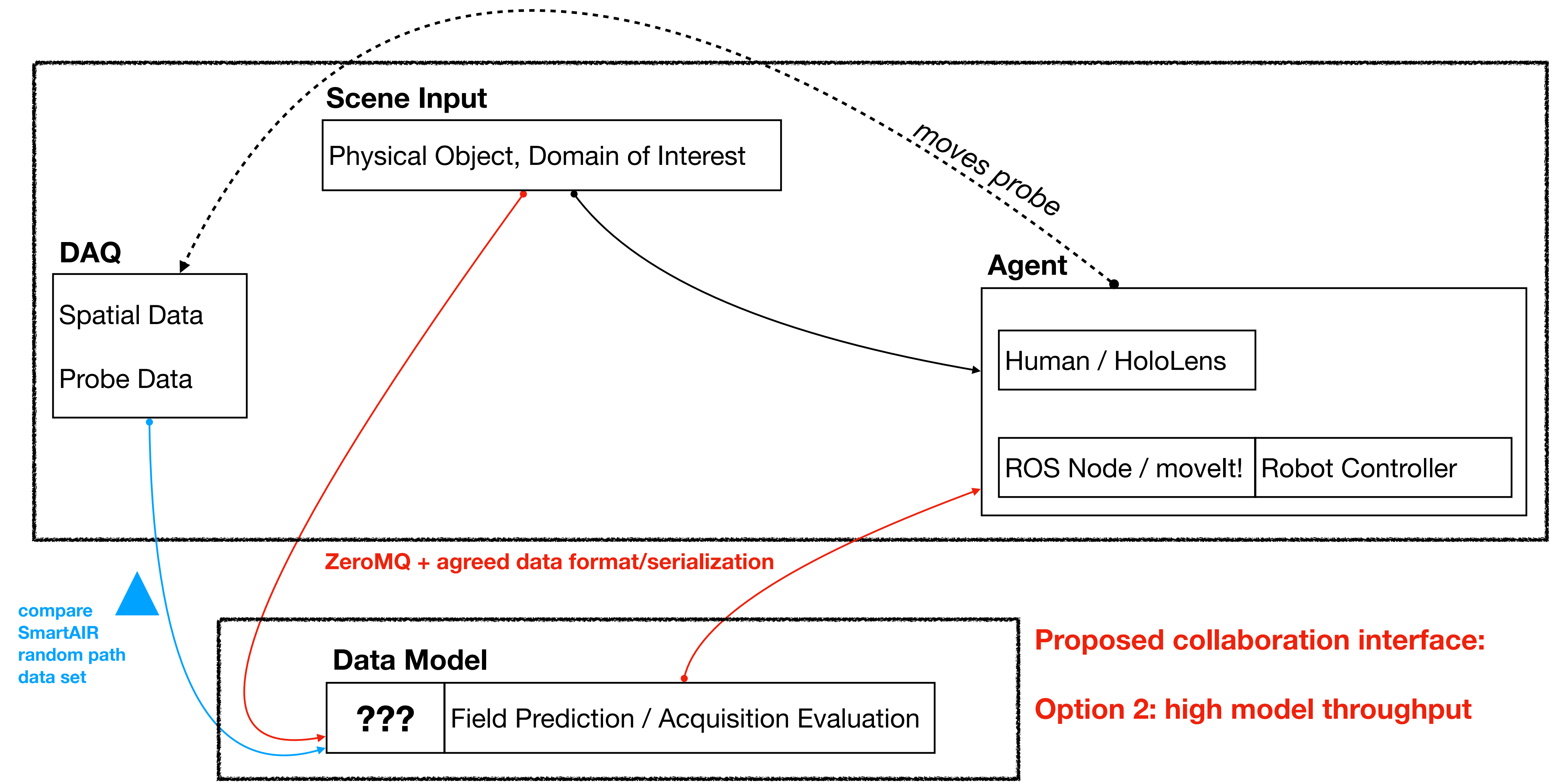


Proposed collaboration interface:

Option 1: low model throughput



Proposed collaboration interface:

Option 2: high model throughput

Data Sets Available

A. Wind Tunnel Measurements

   i. Ahmed Body Traverse

   ii. Ahmed Body SmartAIR “random” path

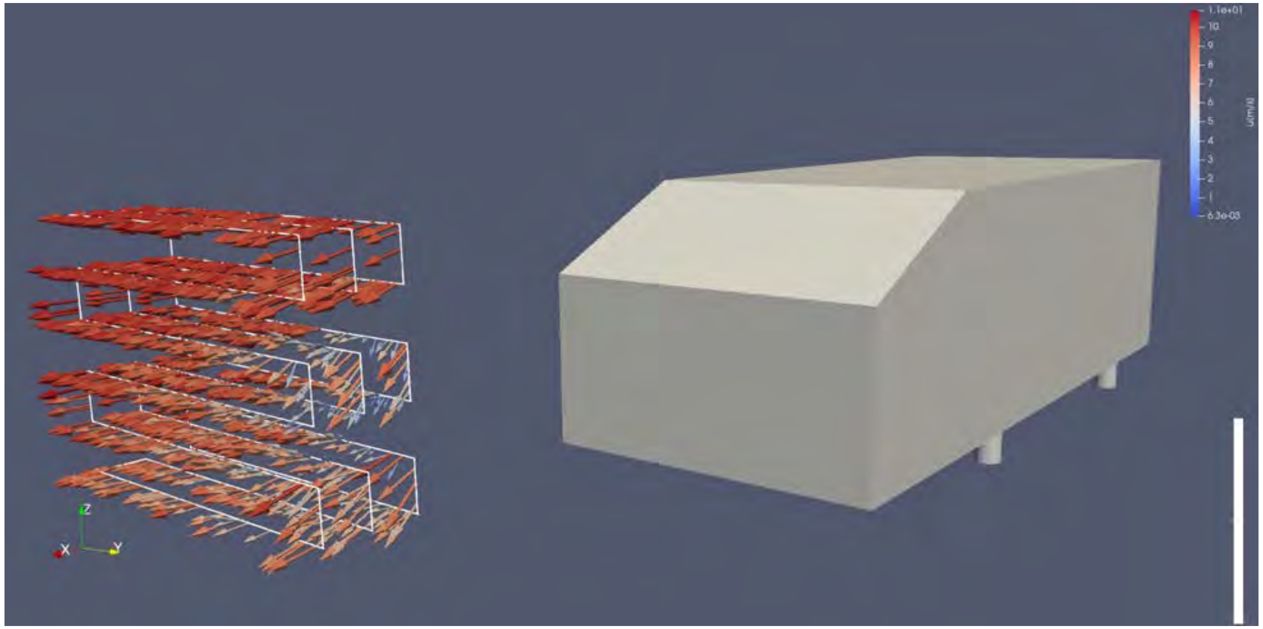
B. Computational Fluid Dynamics (CFD) Simulations

   i. Ahmed Body (3D / stationary)

   ii. Von Kármán Vortex Shedding (2D / non stationary)

Data sets available

A.i.) Ahmed Body Traverse Measurement



Project motivation:

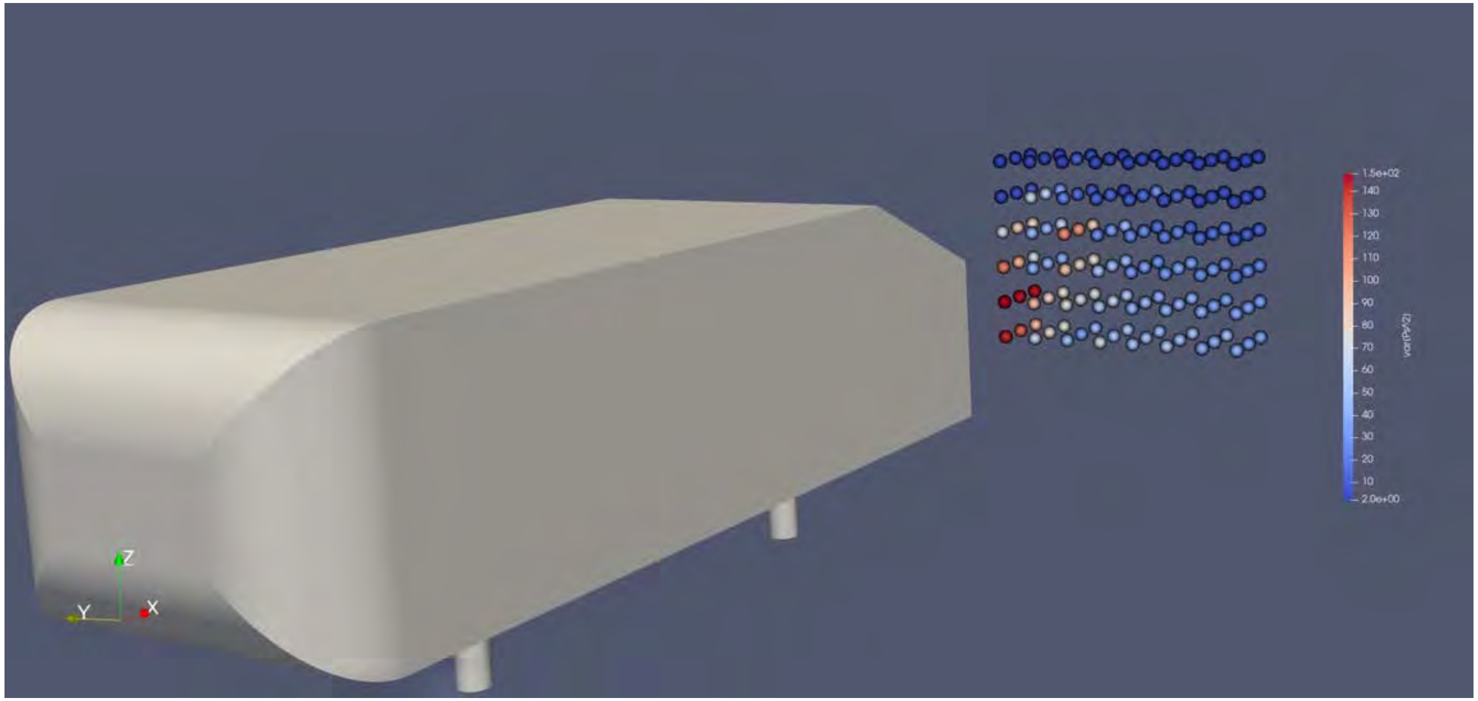
Measurement took 25minutes.
Measure the actual flow, sparse data.
Difficult to visualize and post process.

Compare corresponding CFD case.
Rich data allows extensive post processing. Very difficult to get the physics right.

SmartAIR => short measurement time with data richness comparable to CFD.

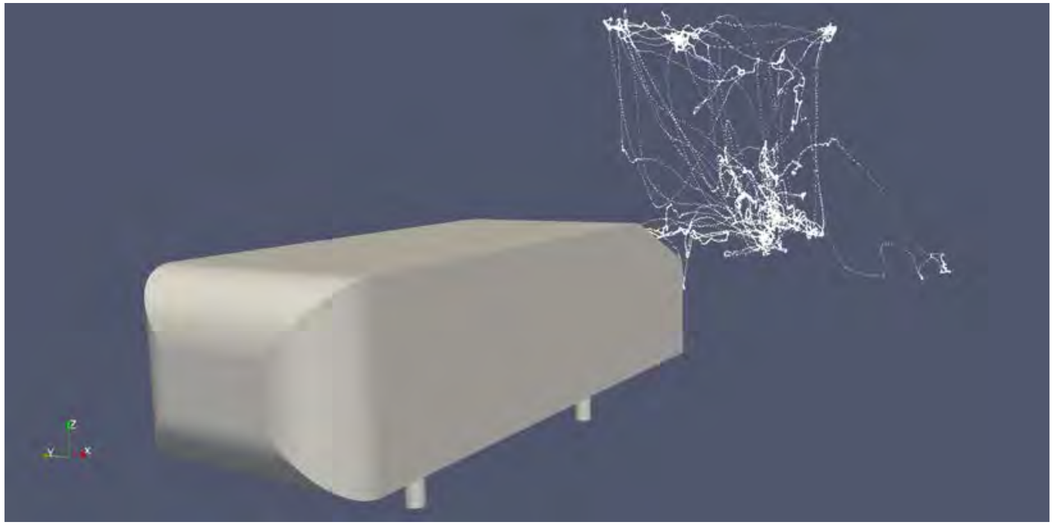
Data sets available

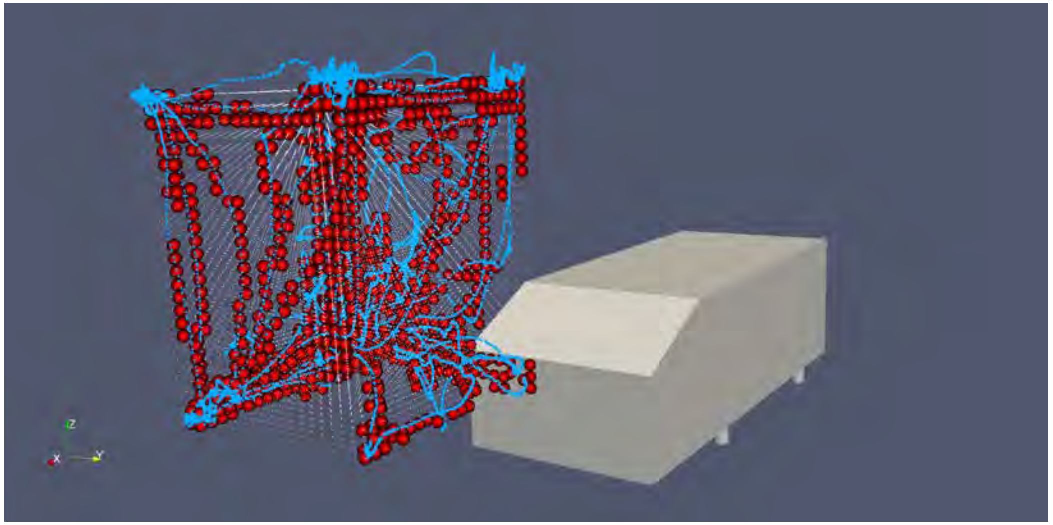
A.i.) Ahmed Body Traverse Measurement — Variance Field



Data sets available

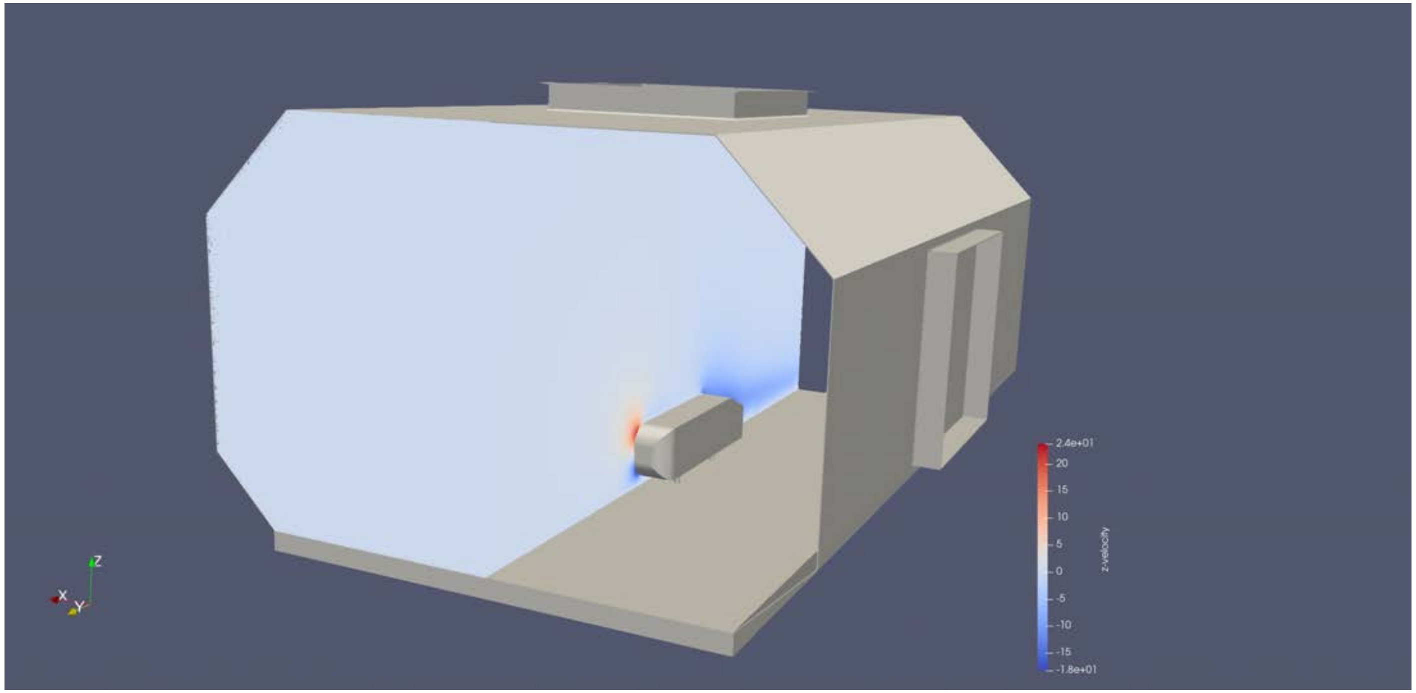
A.ii.) Ahmed Body SmartAIR random path





Data sets available

B.i.) Ahmed Body CFD



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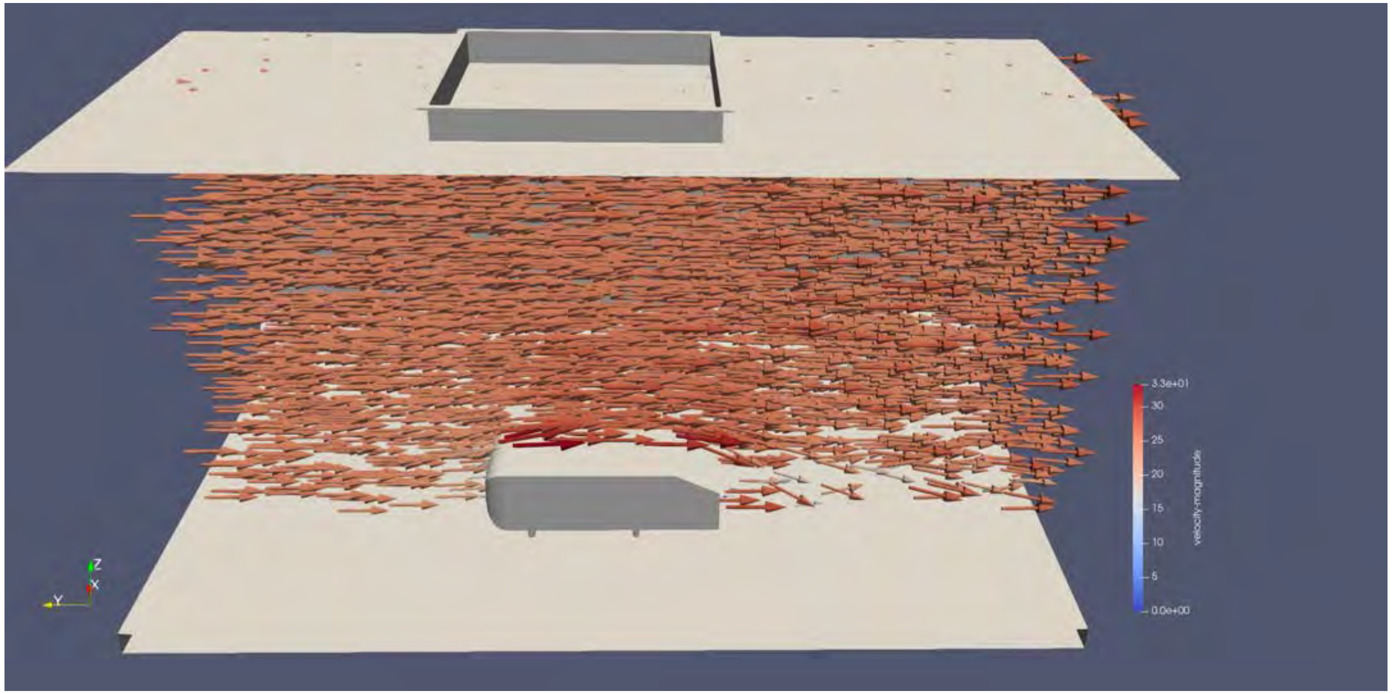

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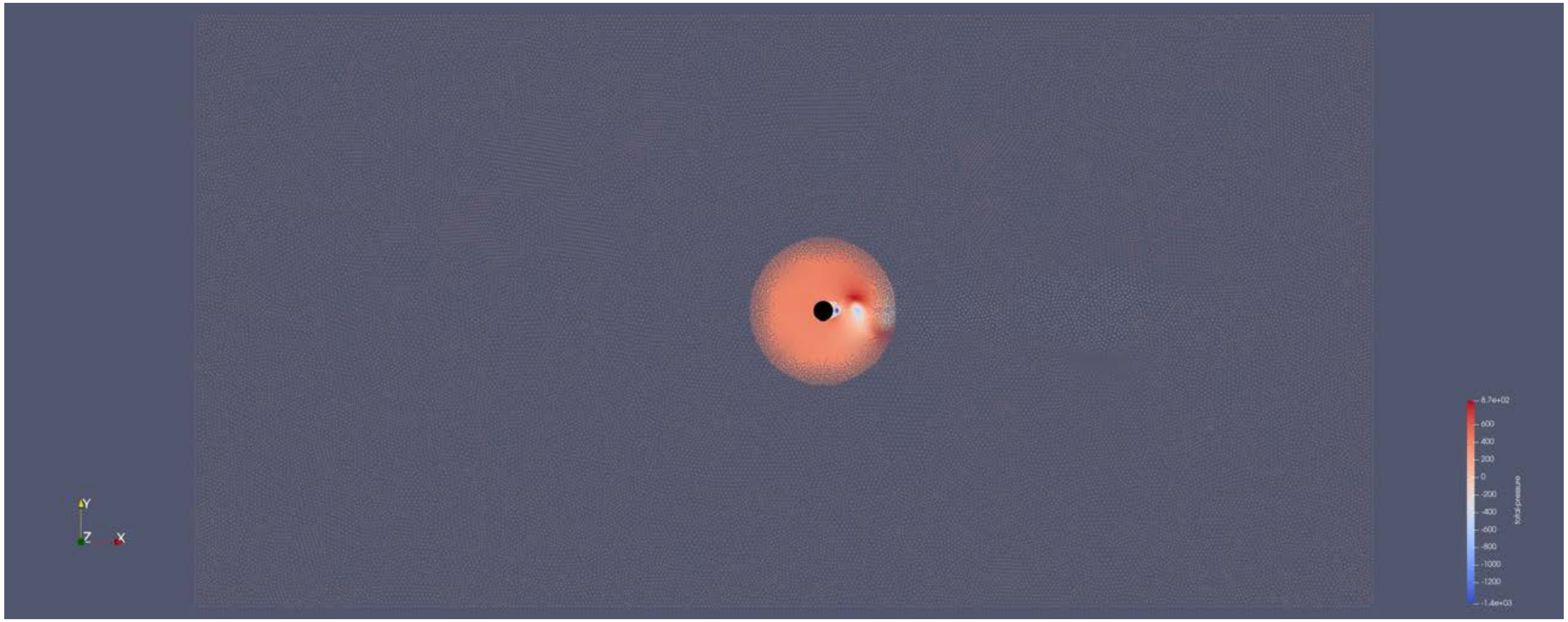

Data sets available

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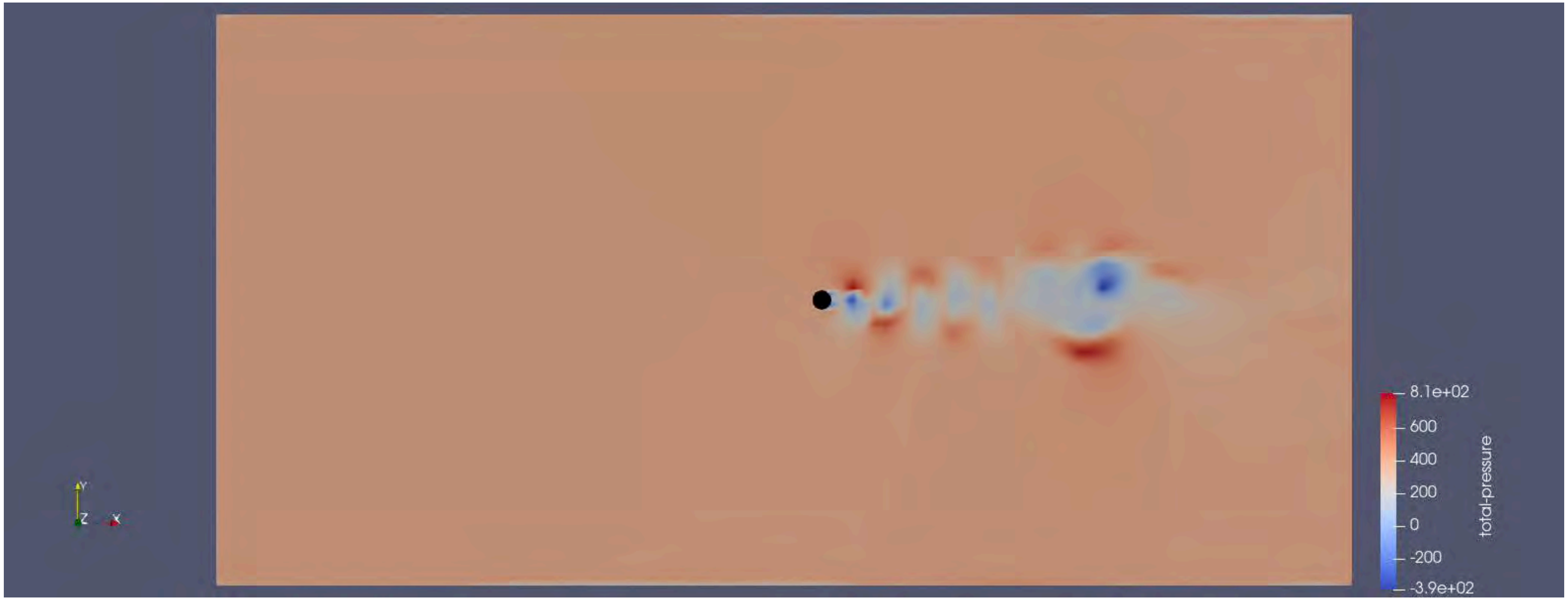
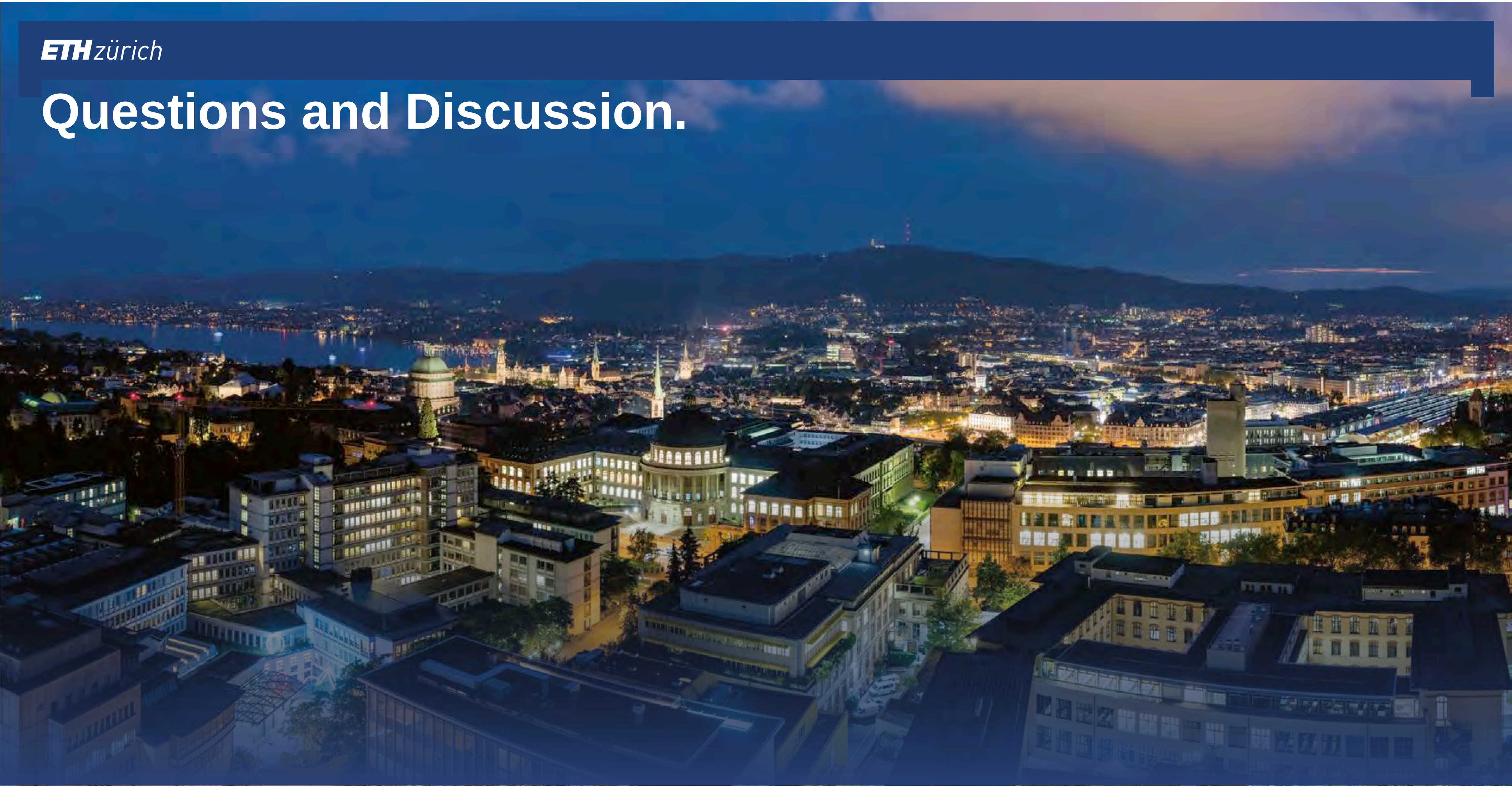


Questions and Discussion.



References:

Müller, A. (2017) Real-Time 3D Flow Visualization Technique with Large Scale Capability. ETH Zurich; Zurich.

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