Intelligent Automation

3DMC 3D METROLOGY CONFERENCE

Loughborough University

16-18th October 2018, Hamburg

Toward Intelligent Automated 3D Measurement

Task Specific Viewpoint Optimisation

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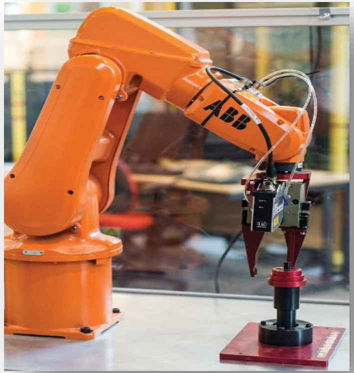
Intelligent
Automation

Centre for Intelligent Automation

Freeform Bolting



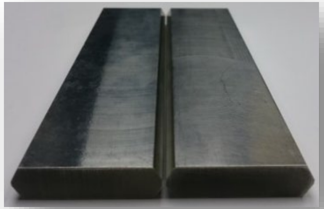
Robotic Assembly

Freeform TIG Welding

Automated Panel Beating

Defect Detection

Robotic Assembly

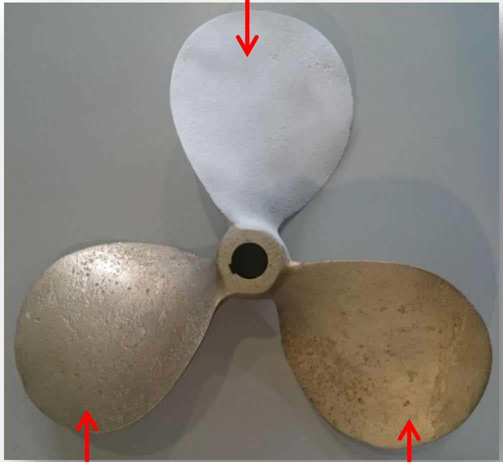


Weld Prep Inspection

Measuring Challenging Surfaces

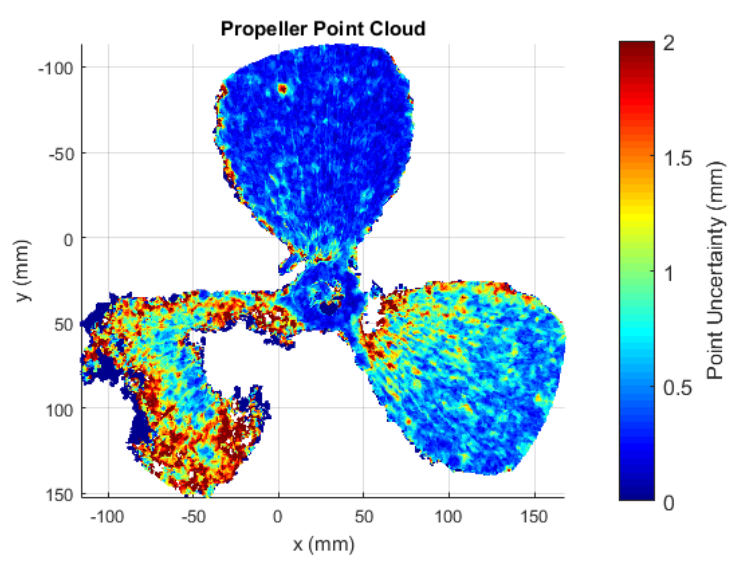
Surface finish, position and orientation affect measurement quality:

Matt Powder Coated



Polished

Grit Blasted



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The Problem

Given an inspection task, what is the optimum pose to perform the measurement?

Pose Reachability

Viewpoint Candidates

Task
- Object localisation
  - Component assembly
  - Bin picking
  - Precursor to feature measurement
- Feature Measurements
  - GD&T Inspection
  - Form Error
- etc.

Object Properties
- Geometry
- Surface finish

Sensor Performance
- Measurability
- Quality

Intelligent Automation

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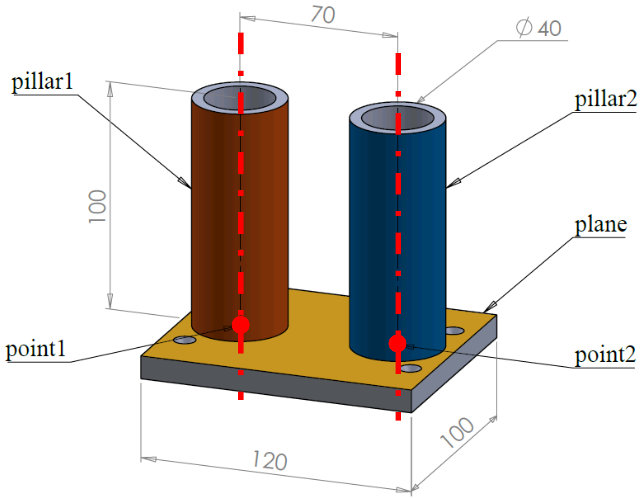
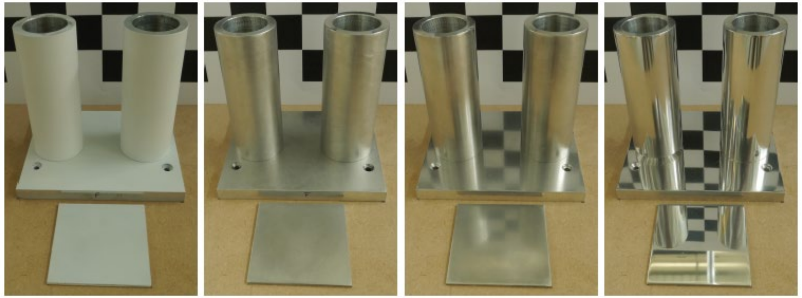
Sample Problem



Measurement	Feature Dependency plane	pillar1	pillar2	Value	Unit
point1_point2_Distance	•	•	•	70	mm
plane_pillar1_Angle	•	•		0	°
plane_pillar2_Angle	•		•	0	°
pillar1_pillar2_Angle		•	•	0	°
pillar1_pillar2_Distance		•	•	70	mm
pillar1_Radius		•		20	mm
pillar2_Radius			•	20	mm



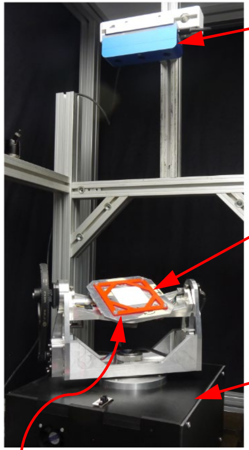
0.74 0.46 0.37 0.09

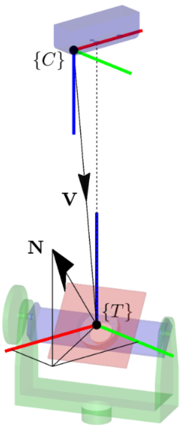
Roughness Average, *Ra* (μm)

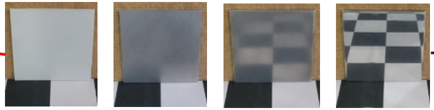
Where are the best places to make the measurements?

- Not all measurements require all features
- Features have conflicting scanning requirements

Our Approach

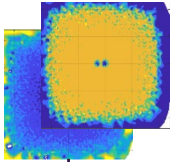




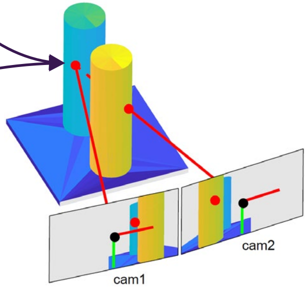


Apply material

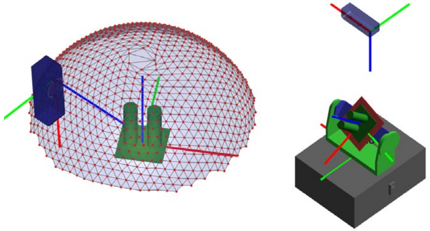
Performance Maps

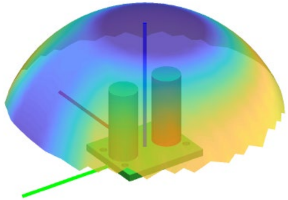


$$F(\boldsymbol{V},\boldsymbol{N},Ra)$$
$$\sigma(\boldsymbol{V},\boldsymbol{N},Ra)$$



Viewpoint Generation





1. Sensor Characterisation
- distance |**V**|
- normal **N**
- Roughness *Ra*

Process point cloud only

2. Sensor Modelling

Predict noise and density of the point cloud

3. Viewpoint Scoring
- Create a feature measurement score
- Combine feature scores per measurement and view

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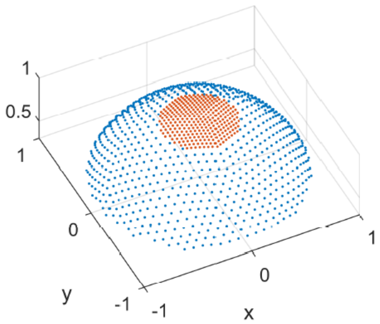
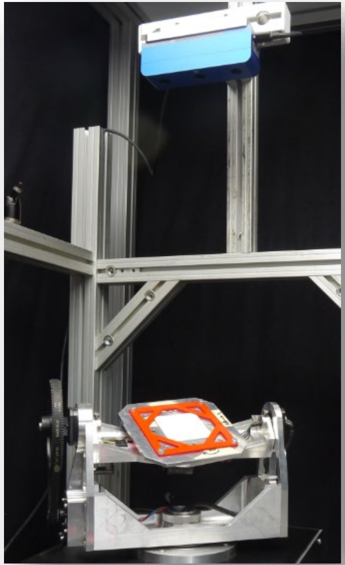
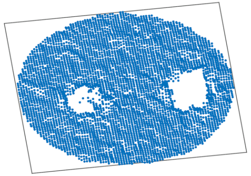
Sensor Characterisation

Data Collection

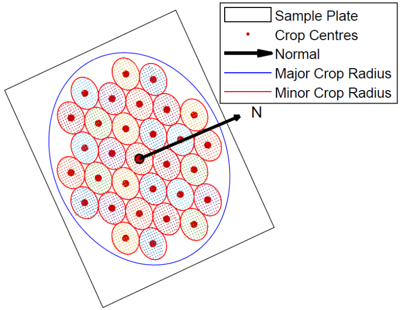






Gloss White

Aluminium
$Ra = 0.4\mu m$



1. Generate Sample Poses

- Sub-divide icosahedron
- Variable density

2. Collect Data

- Run poses
- Vary sample and distance

3. Segment Point Clouds

- Sub segment point cloud with variable minor radius
  - maintain nPoints
  - Reduce included angle

Point Cloud Processing

For each sub point cloud:

Fraction of Recovered points, F:

$$F = \frac{denstity\ of\ recovered\ points}{maximum\ possible\ density\ of\ points}$$

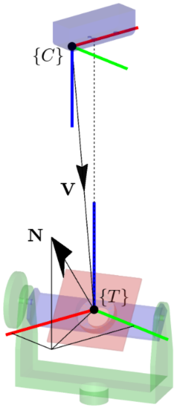
Normalised for distance, $|\boldsymbol{V}|$, and surface angle, $\widehat{\boldsymbol{N}} \cdot \widehat{\boldsymbol{V}}$, so isolates the effect of surface finish on performance

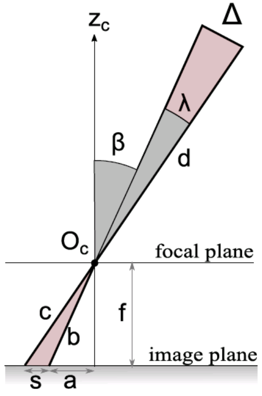
$$\rho = \lambda^2 \frac{n|\boldsymbol{V}|^2}{A(\widehat{\boldsymbol{N}} \cdot \widehat{\boldsymbol{V}})}$$

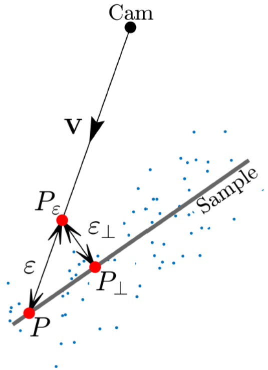
Point standard deviation, σ (mm):

Measured along $\boldsymbol{V}$ to plane – the actual direction of noise propagation

$$P = P_\varepsilon + \varepsilon \widehat{V}$$

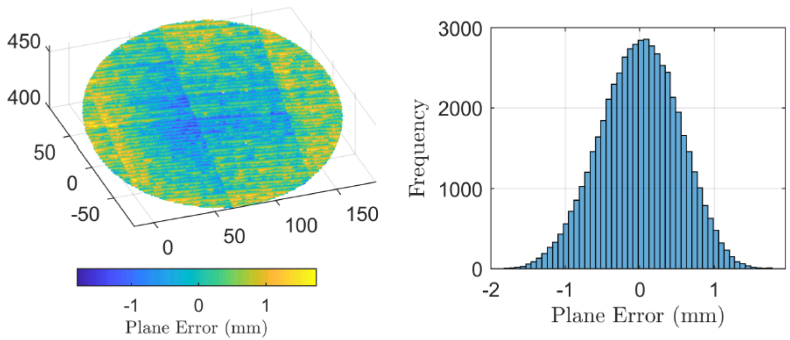




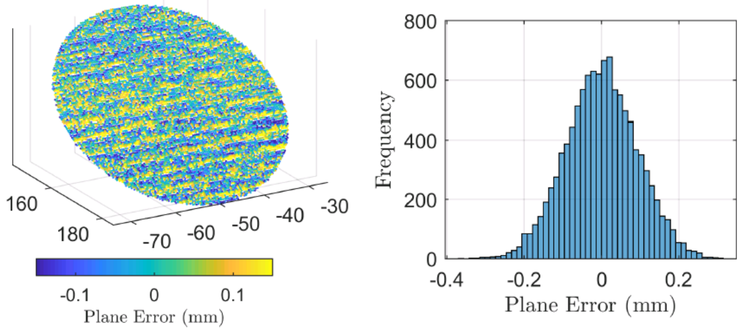


Sensor Characterisation

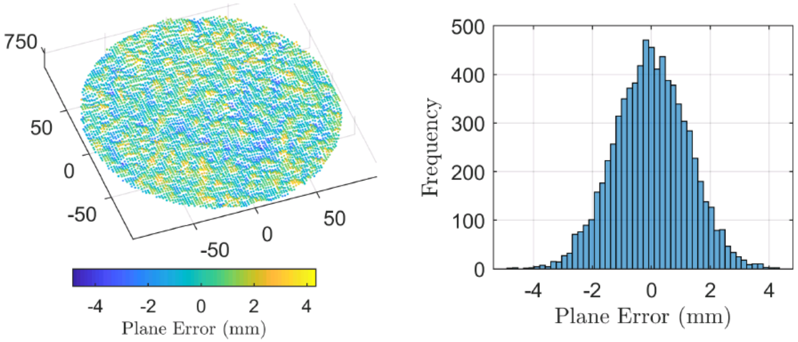
Noise Distributions



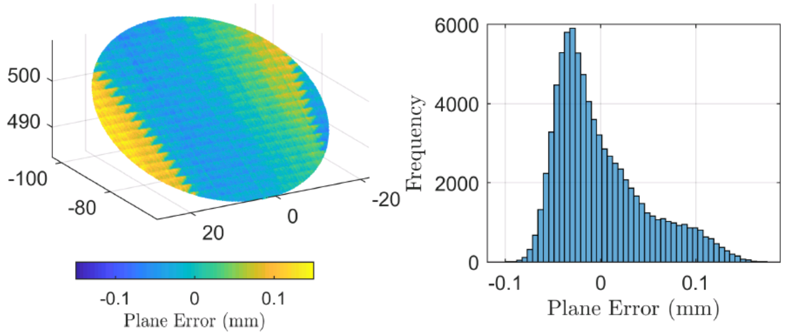
PrimeSense Carmine 1.09



PhotoNeo S

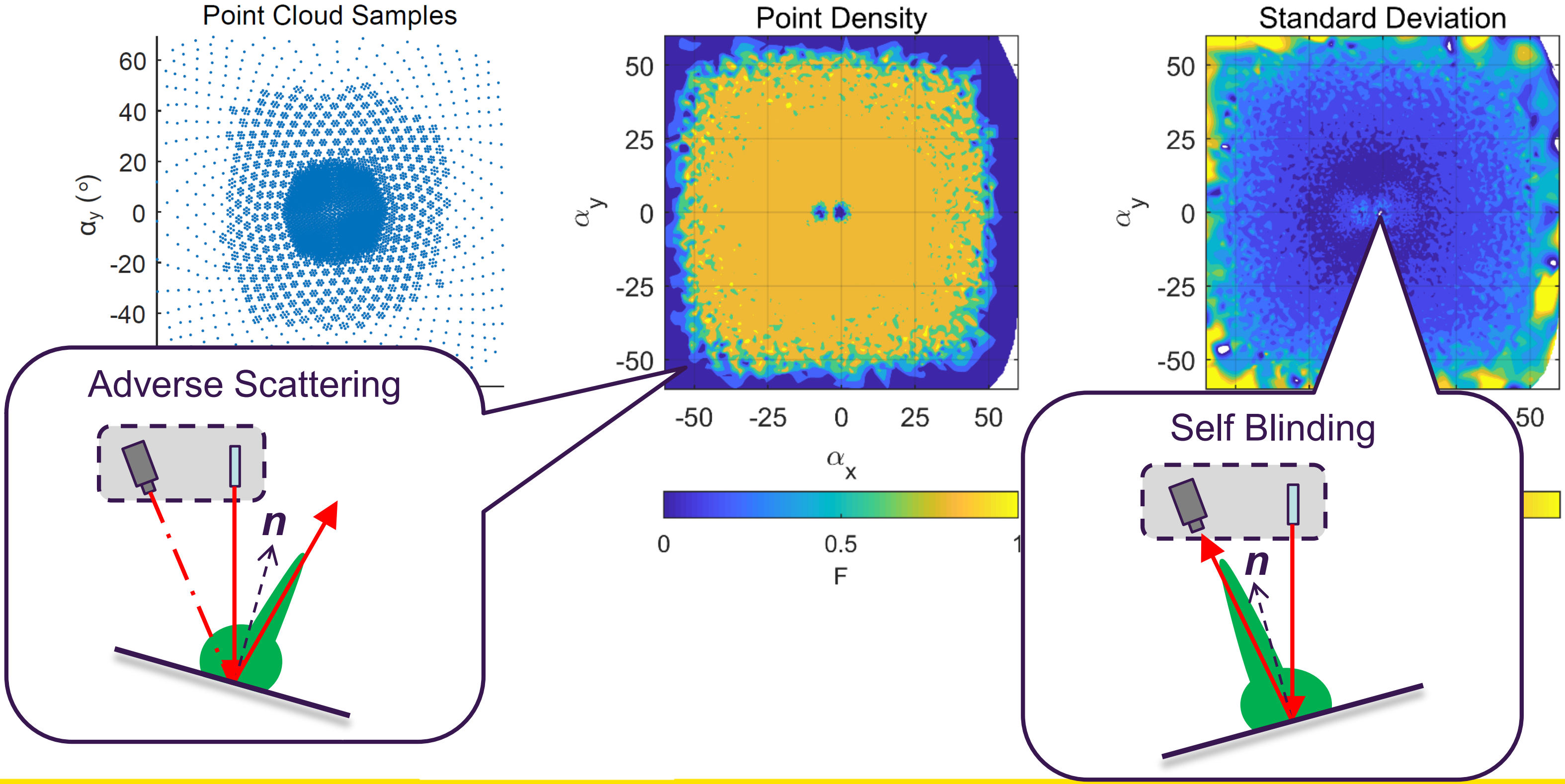


Microsoft Kinect V2



David SLS 3

Results – Ensenso N10



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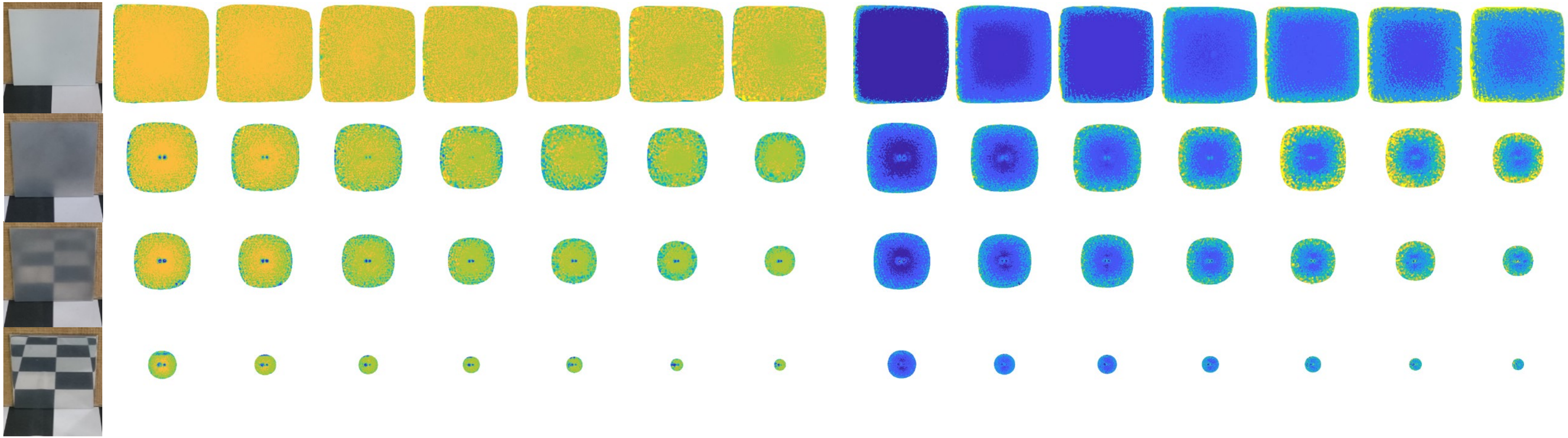
Performance Maps

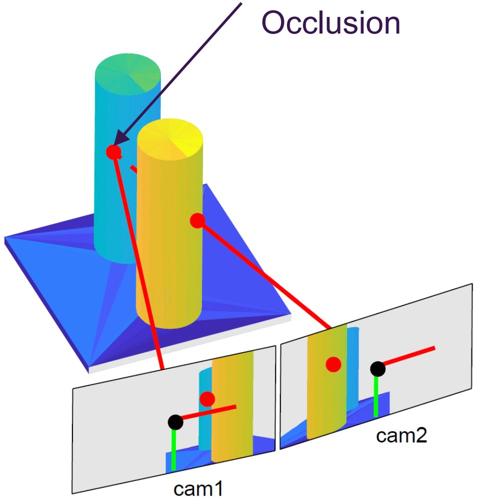
Point Fraction — Distance: 400 mm → 800 mm

Standard Deviation — Distance: 400 mm → 800 mm

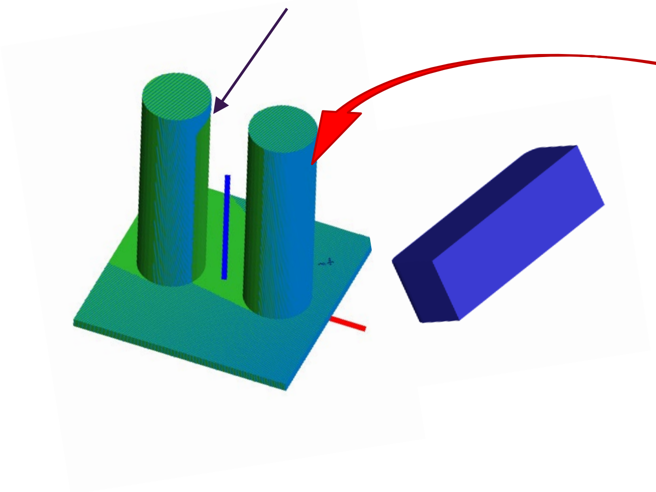


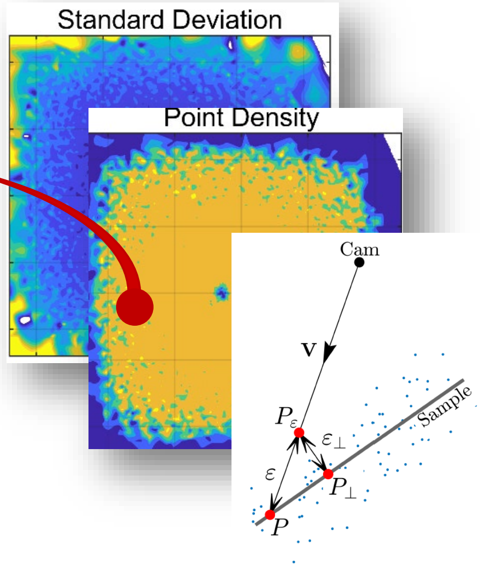
Simulating the Point Cloud

Account for Multi-Camera Occlusion



Apply Material to Model Faces





1. Sensor Model
   - Requires camera geometry
   - Standard graphical methods:
     - Frustum & back face culling
     - Ray-tracing occlusion determination

2. Ideal Point Cloud
   - Perfect intersection of rays and model faces.

3. Apply Noise & Uncertainty

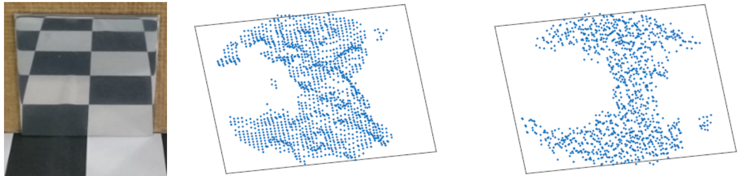
$$\varepsilon = R_N \sigma_e$$

$$\boldsymbol{P}_\varepsilon = \begin{cases} \boldsymbol{P} + \varepsilon \widehat{\boldsymbol{V}}, & if\ R_U < \rho_e \\ [], & otherwise \end{cases}$$

Simulation Validation

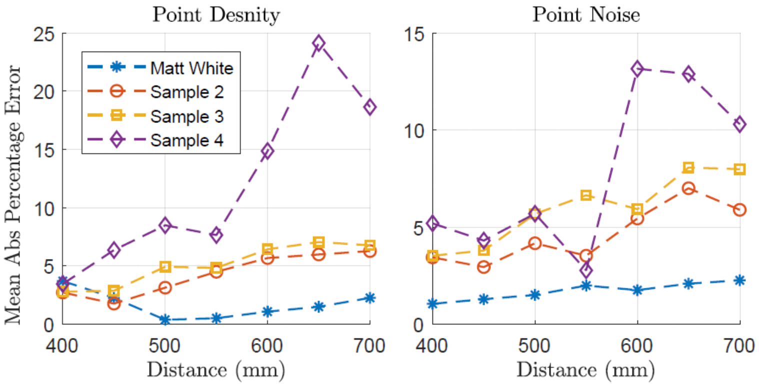
Simulate point clouds corresponding to characterisation data set.

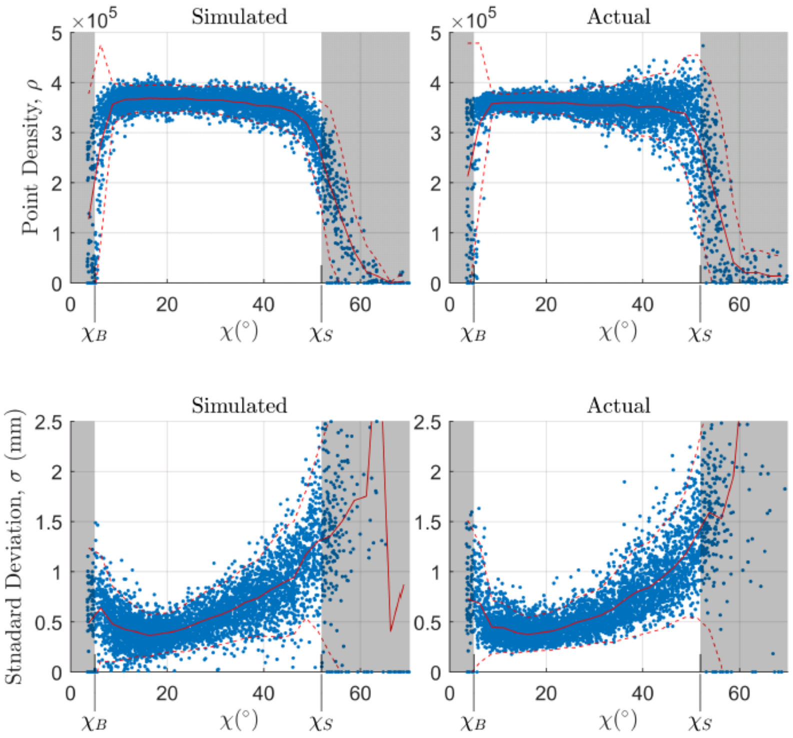
Sample 4
@ 600 mm



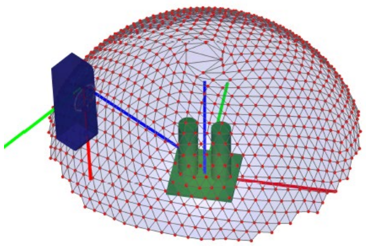
Actual

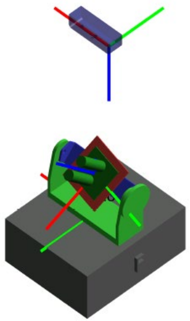
Simulation

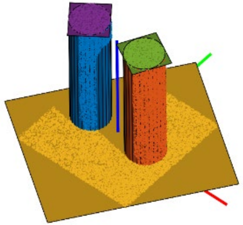


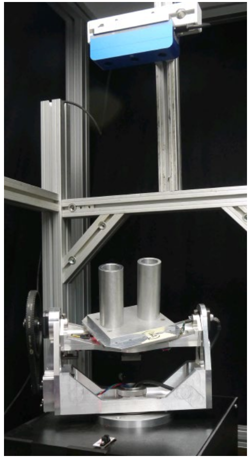


Viewpoint Scoring

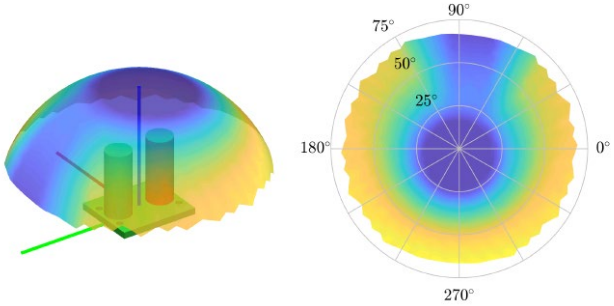








Number of points for *pillar2*



(a) 3D Heatmap (b) Polar Heatmap

1. Generate candidate views
   - Sub divide icosahedron to sample a sphere.
   - Ensure reachability by the tilt table

2. Simulate & Measure Views
   - Segment point cloud on feature basis
   - Calculate feature scores

3. Score Views per Measurement

Combine feature scores based on:
- Fraction of points recovered
- Mean point noise
- Feature occlusion ratio

The View Score

We assume that feature accuracy improves with:

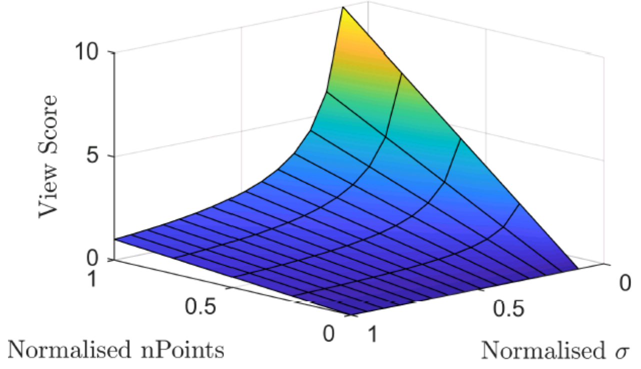
- More acquired points
- Lower point noise
- More feature visibility

Feature Score, S_f

$$S_f = \left(\frac{\hat{n}}{\hat{\sigma}}\right)_f$$

$$\hat{n}_f = \frac{n_f}{\max(n_f)_{MattWhite}}$$

$$\hat{\sigma}_f = \frac{\bar{\sigma}_f}{\max(\bar{\sigma}_f)_{MattWhite}}$$



Feature Occlusion Ratio

$$R_f = \left(\frac{n}{n_{only}}\right)_{f,\,MattWhite}$$

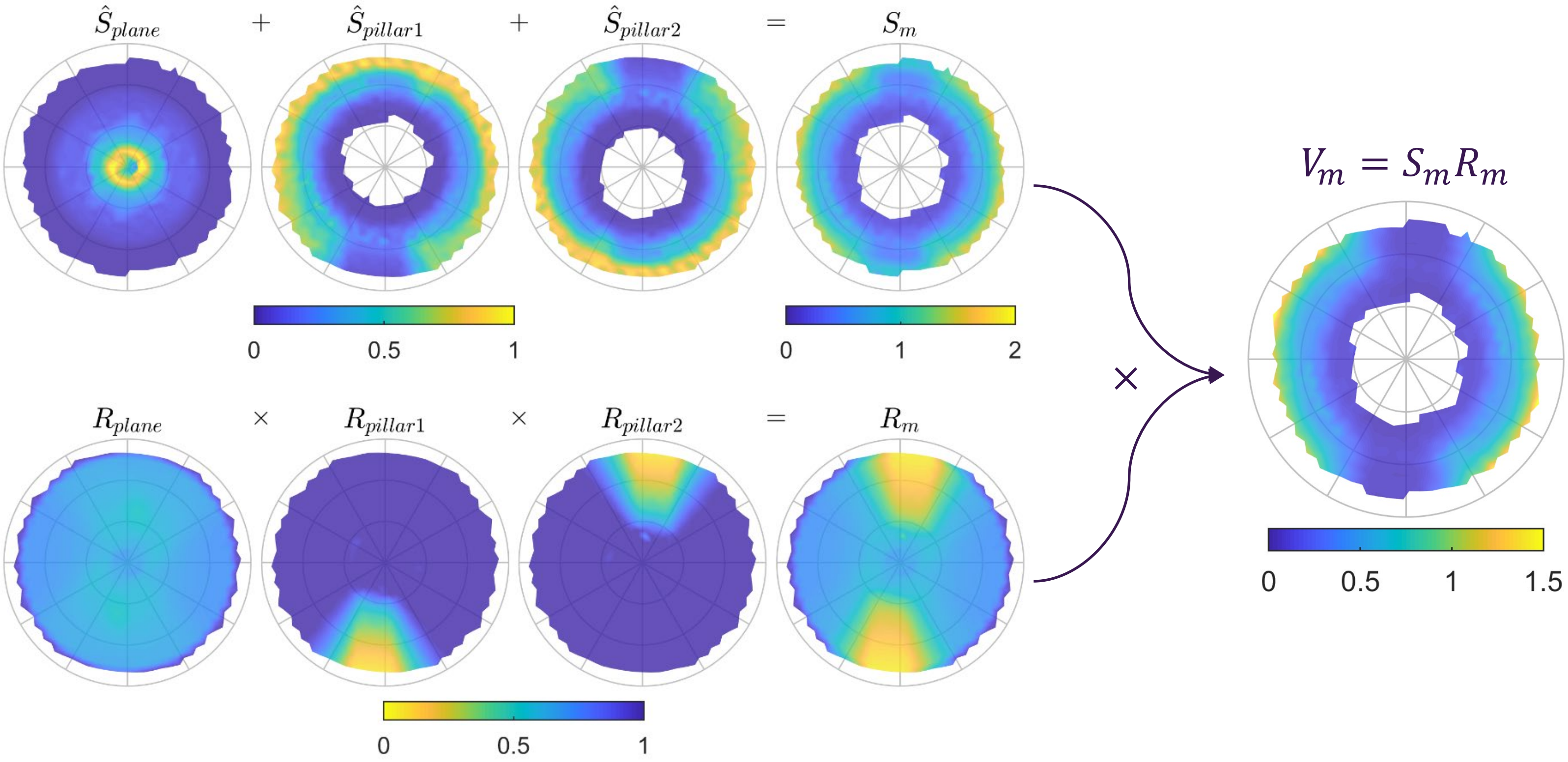
n_f = number of points for feature f

The View Score

All feature measurement, $F_m \in (plane, pillar1, pillar2)$

$$S_m = \sum_{f \in F_m} \hat{S}_f$$

$$R_m = \prod_{f \in F_m} R_f$$



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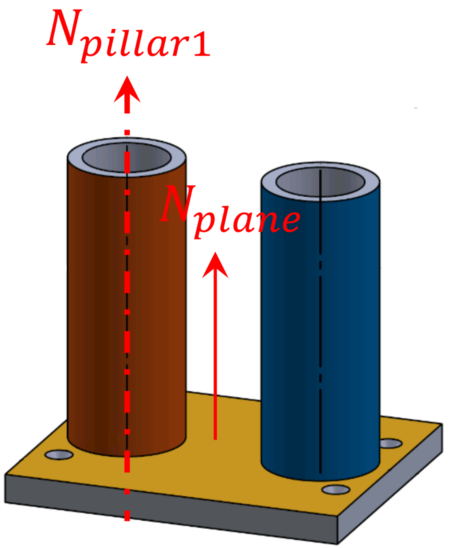
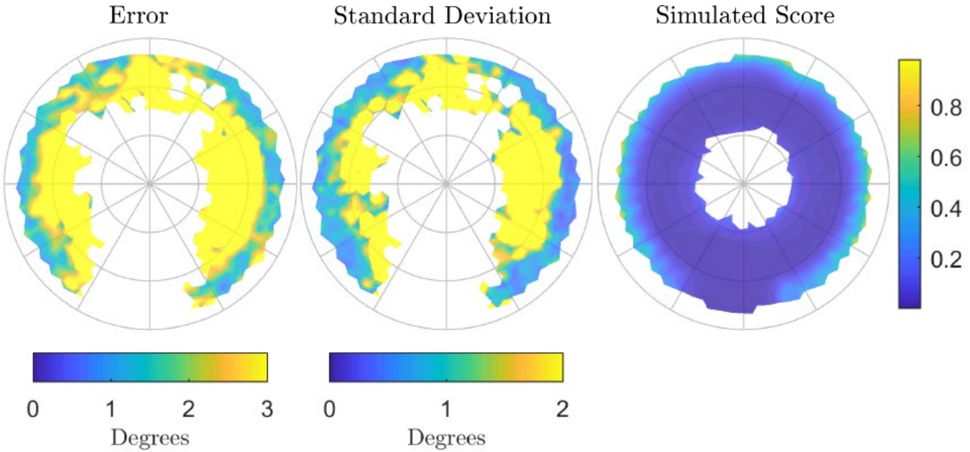
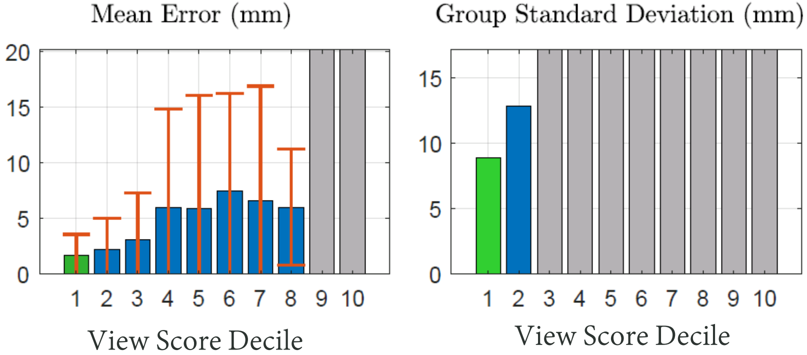
Example Result

$plane \rightarrow pillar1\ Angle$



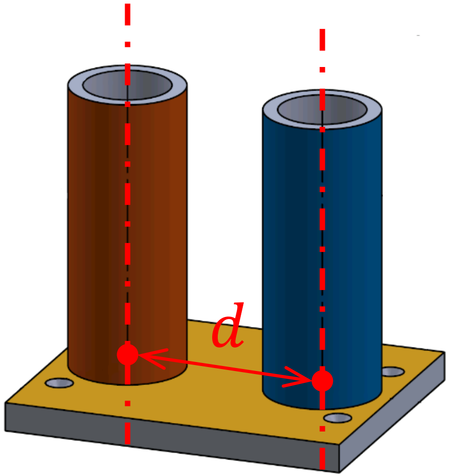
$$\theta = \angle N_{pillar1} N_{plane}$$

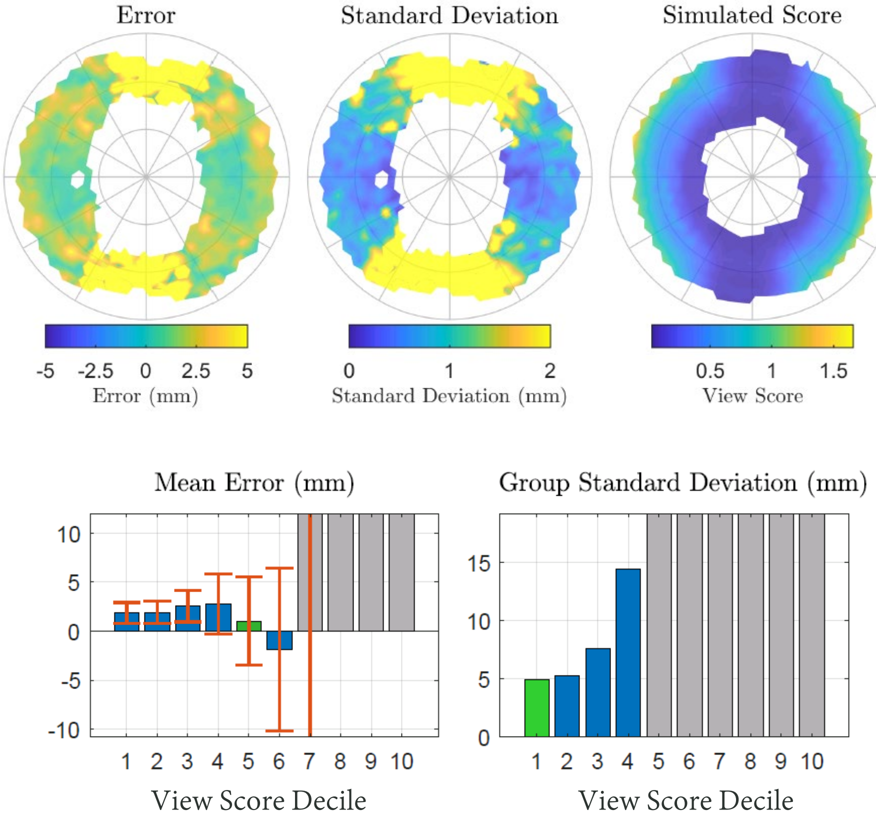




Example Result

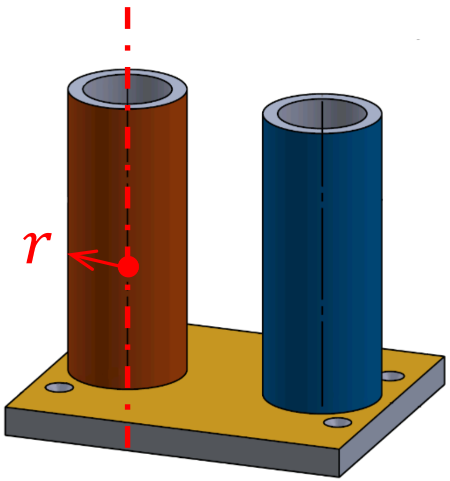
$point1 \rightarrow point2\ Distance$

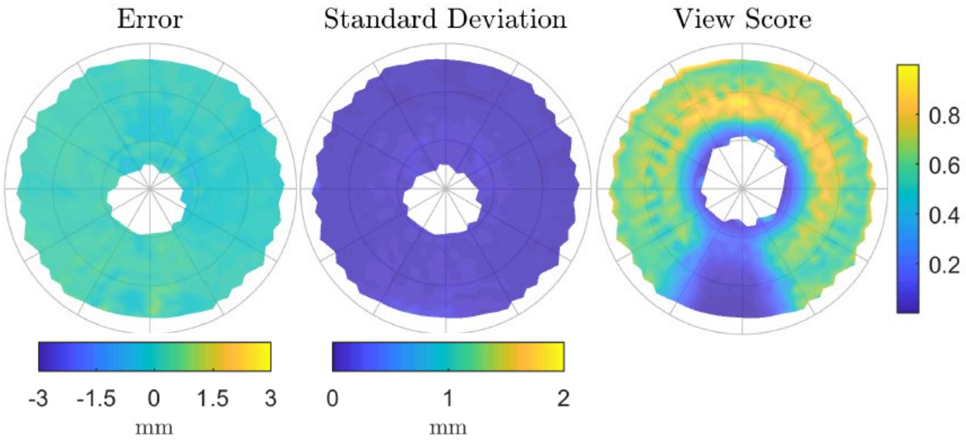


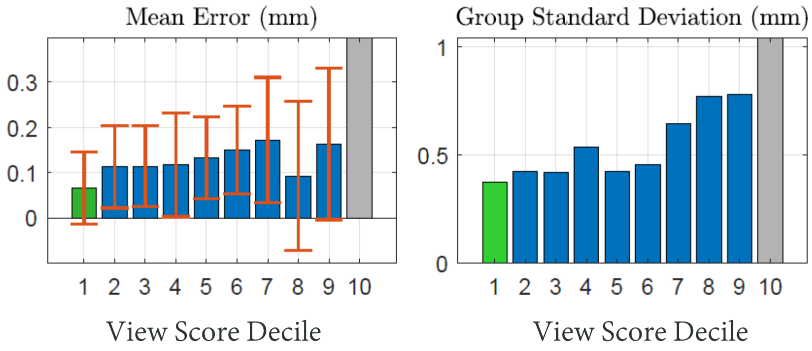


Example Result

$pillar1\ Radius$

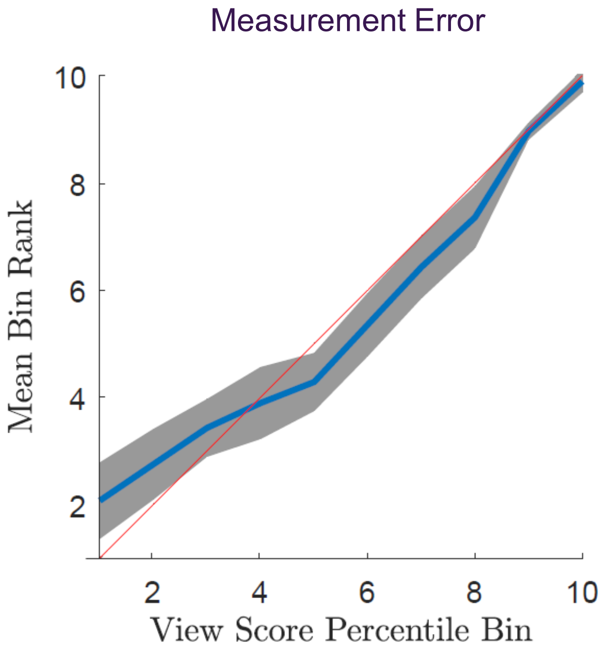


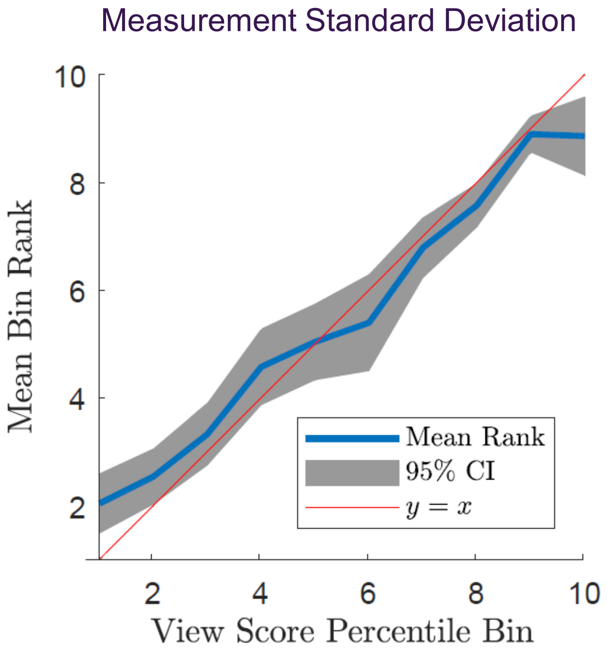




View Score Accuracy

Mean rank of the view score percentile bins for every measurement and sample





Summary

- Sensor characterisation method
  - Allows **real-world sensor performance** comparison.
  - Provides an empirical **sensor performance model**.

- Sensor simulation
  - Use **model to predict point cloud quality**.
  - Simulate measurement tasks

- View optimisation
  - Predict optimum **measurement specific** pose scores.