Supported by:

Federal Ministry for Economic Affairs and Climate Action

ZIM Zentrales Innovationsprogramm Mittelstand

on the basis of a decision by the German Bundestag

TECHNISCHE HOCHSCHULE DEGGENDORF THD

Technologie Campus Cham

Automated Powder Removal and Handling of Powder-Printed Parts

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Internationale Forum Mechatronik
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Outline

TECHNISCHE HOCHSCHULE DEGGENDORF
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- Background
- Methodology
- Results
- Conclusions

Background

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„AutoClean“ Project:

This Project is supported by the Federal Ministry for Economic Affairs and Climate Action (BMWK) on the basis of a decision by the German Bundestag.

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TECHNISCHE HOCHSCHULE DEGGENDORF
Technologie Campus Hutthurm

SHL Automatisierungstechnik

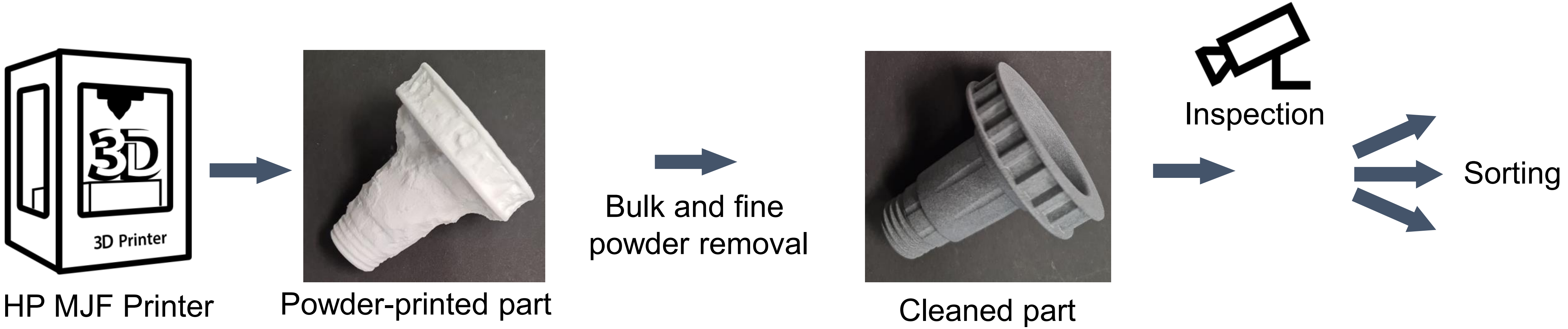
thinkTEC 3D

Project Partners:

- THD: TC Cham (Control and Automation), TC Hutthurm (Simulation)
- thinkTEC 3D GmbH (Additive Manufacturing)
- SHL AG (Automation)

Background

„AutoClean“ Project:
Automate post-processing of powder printed parts to remove powder, inspect and sort them.



Processes in „AutoClean“:

- After HP Multi-Jet-Fusion (MJF), excess white unprocessed powder from the parts.
- Autonomous grasping and transfer of parts to other stations.
- Bulk powder removal and fine powder removal mechanisms.
- Rotation of part in front of inspection camera, while most of the surface visible.

Background

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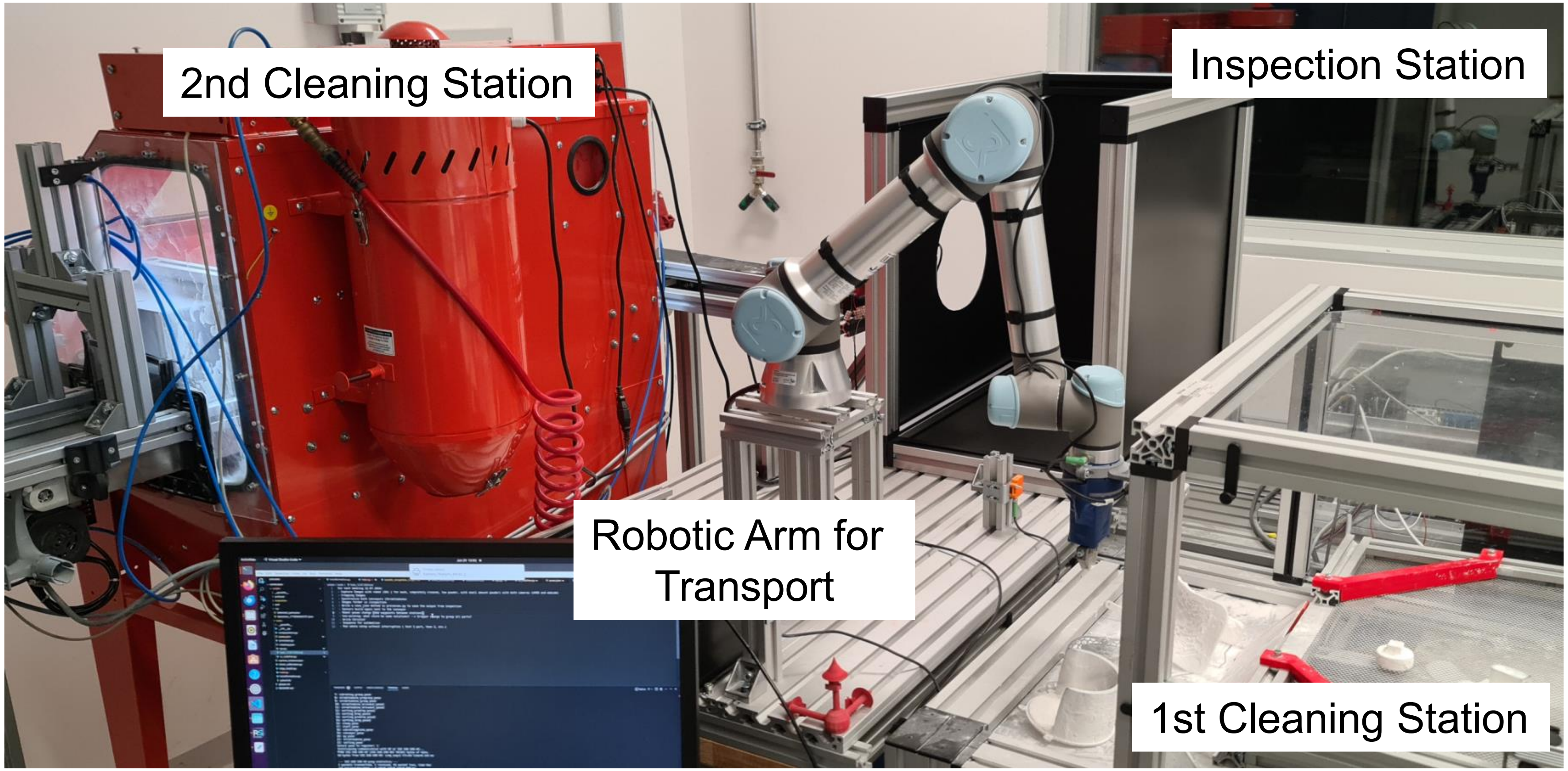
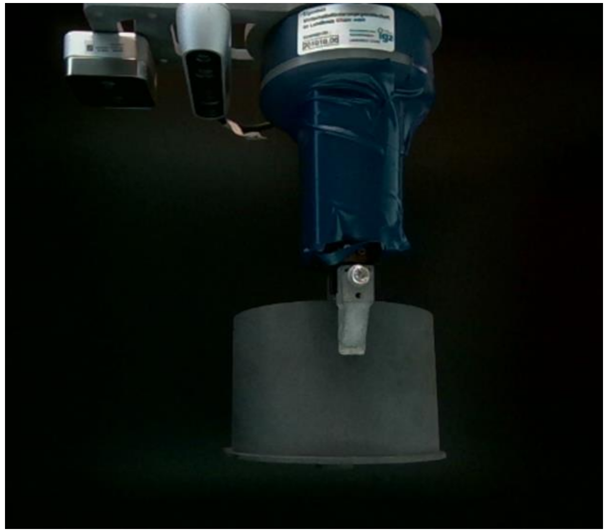
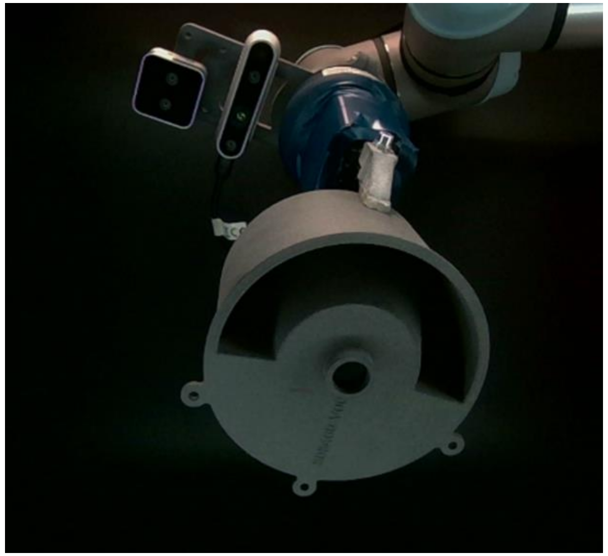


AutoClean Layout





Inspection Process

Breakdown of Methodology and Algorithm: Printed Parts

1. Powder-printed parts

- Experimented with a set of 12 printed parts with random geometries.

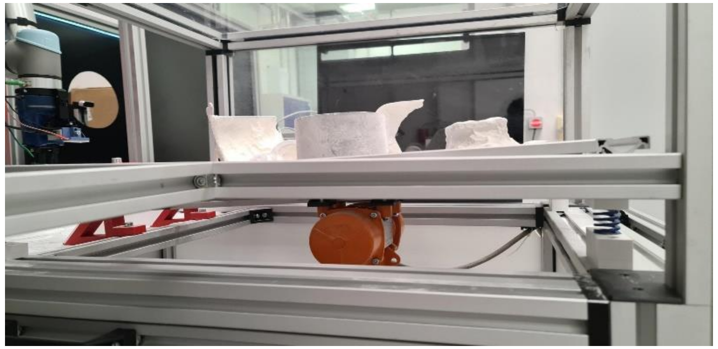
Sample of powder-printed parts (powdered to powder-free)

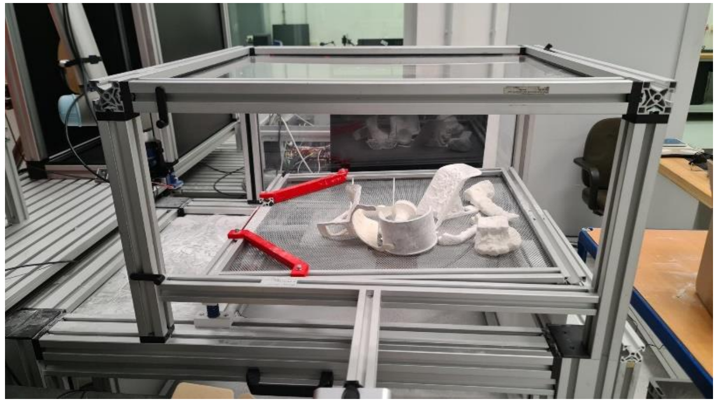
- Parts with varying degrees of powder were used: from fully powdered to partially powder-free.
- Parts were fed at different rates through the automated post-processing setup.
- Images were captured from multiple perspectives to register most possibilities for grasping.

Breakdown of Methodology and Algorithm: Printed Parts

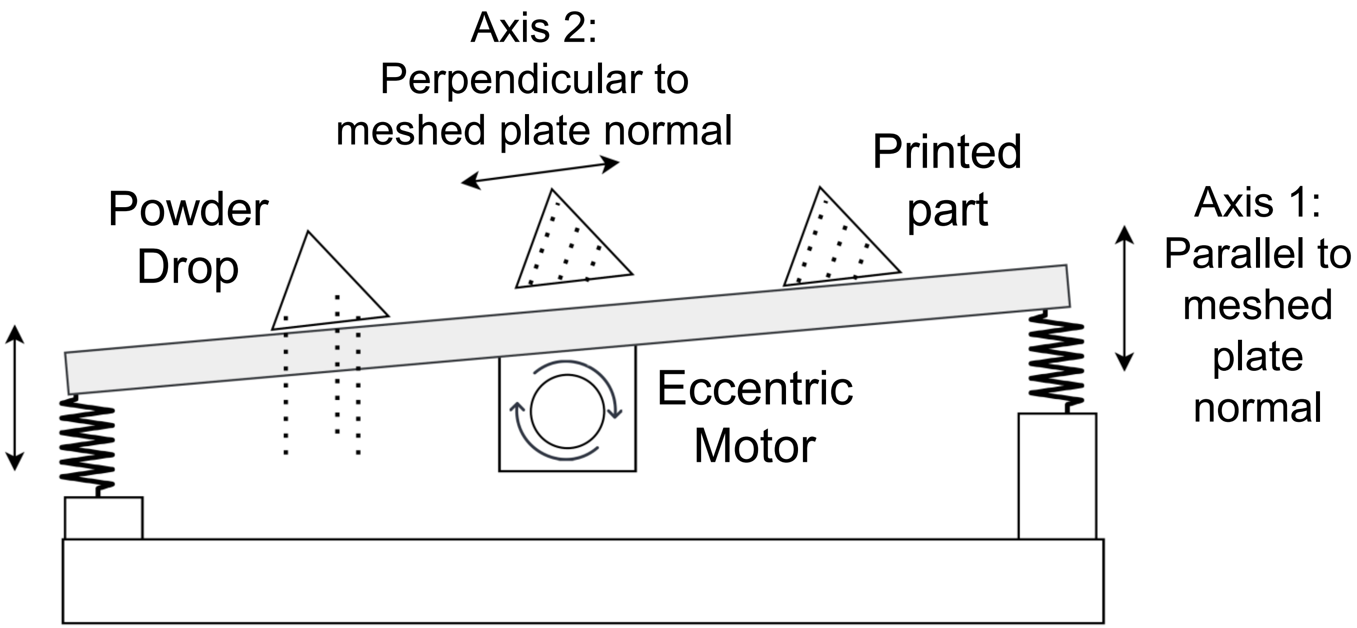
1. Powder-printed parts: Bulk Powder Removal

- Meshed plate coupled to an eccentric motor
- Motor spin parameters:
  - Spin frequency (20 Hz to 50 Hz)
  - Spin direction (Clockwise and Anticlockwise)
- Powder removal through momentum between meshed plate and parts





Vibrating Plate Setup



Vibrating plate: 2-axis control of parts based on vibration frequency and direction

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2. Convolutional Neural Networks

A Region of Interest (ROI) is identified by a CNN model, which in this case is a YOLOv7 CNN with CSPDarkNet-53 Backbone [4].

<u>YOLO</u> <u>(You Only Look Once)</u> **<u>CNN</u>**:
recognize patterns in images, by passing the image through a series of filters that highlight different features (shape, color, shades, etc.).

Parameter	YOLOv4	YOLOv7
Learning rate	0.001	0.003
Maximum batches	8000	6000
Batch Size, Subdivisions	64, 8	8, 1
Filters	21	21
Network Size	608 x 608	640 x 640

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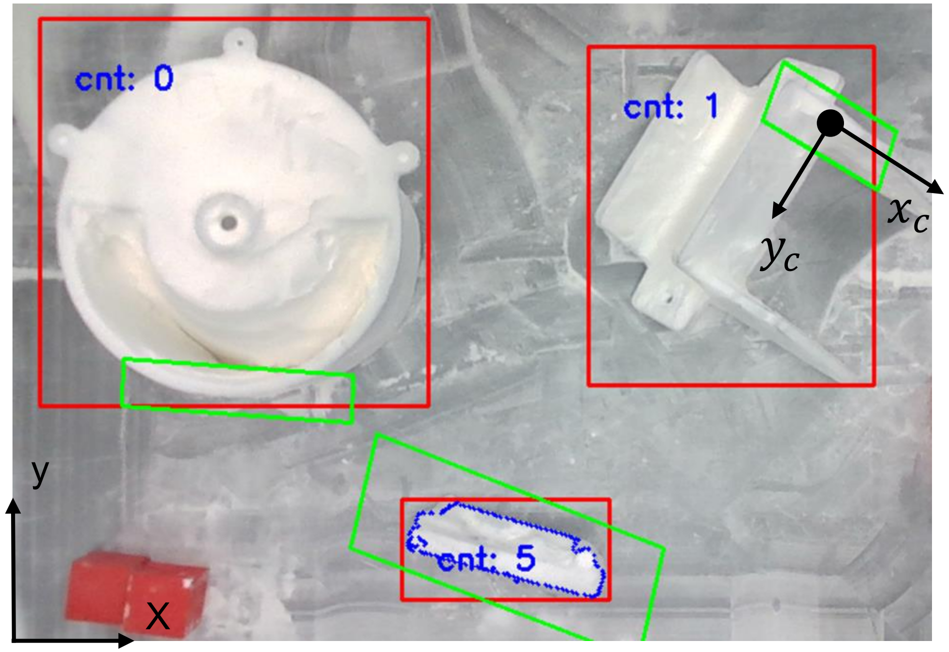
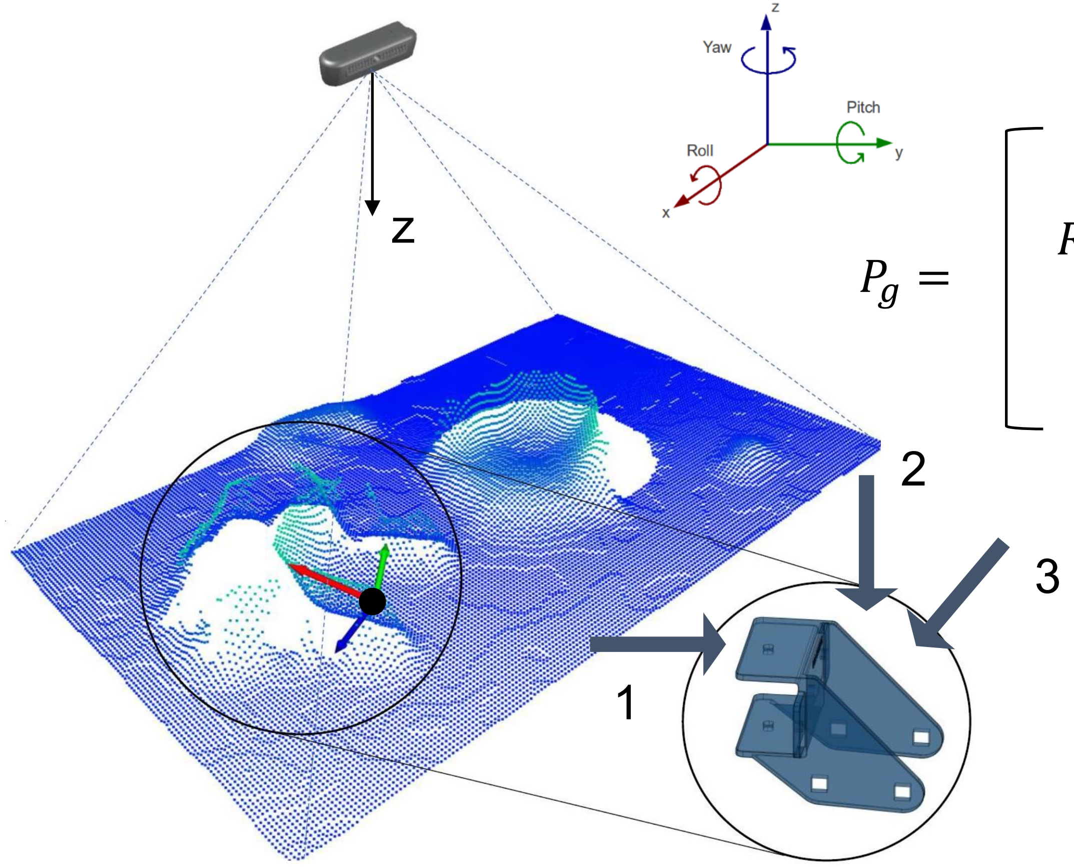
3. 6D edge pose detection

First obtain a 4 DoF pose (using conventional Canny edge detection) which narrows down the region for a 6 DoF pose, which gives the manipulator a specific pose for grasping edge *j*.



Representation of 4 DoF Grasp

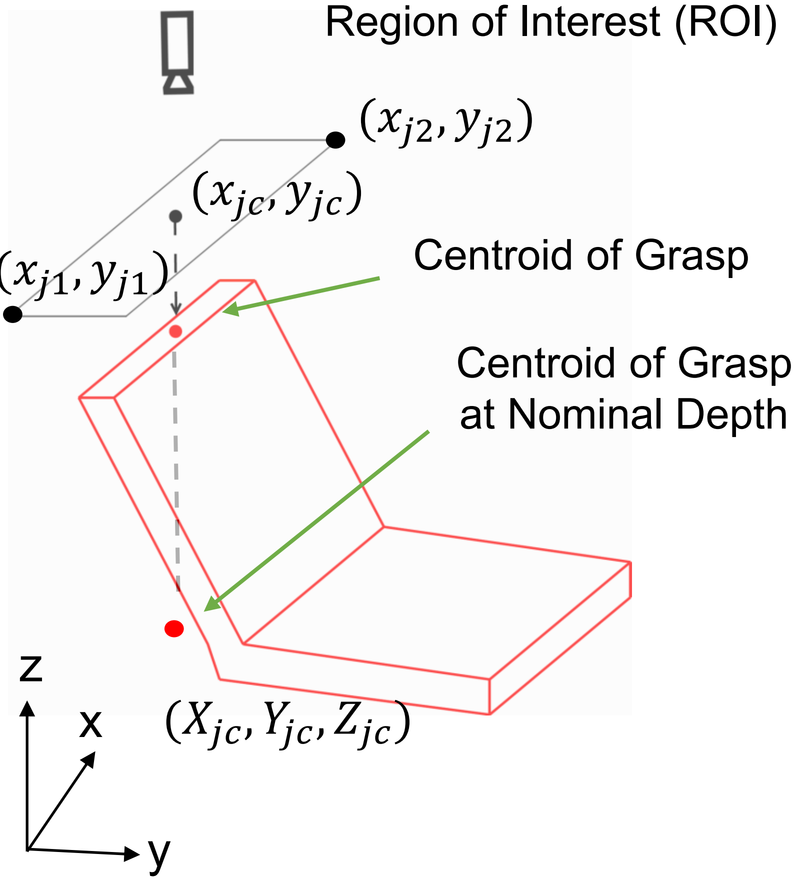
$$P_c = \begin{bmatrix} x_c \\ y_c \\ z_c \\ R_z \end{bmatrix}$$



$$P_g = \begin{bmatrix} & X_c \\ R_g & Y_c \\ & Z_c \\ 0 & 1 \end{bmatrix}$$

Representation of Possible 6 DoF Grasps

4. Point Cloud processing



Consider an **edge j**,

$$centroid_j = (x_{jc}, y_{jc})$$

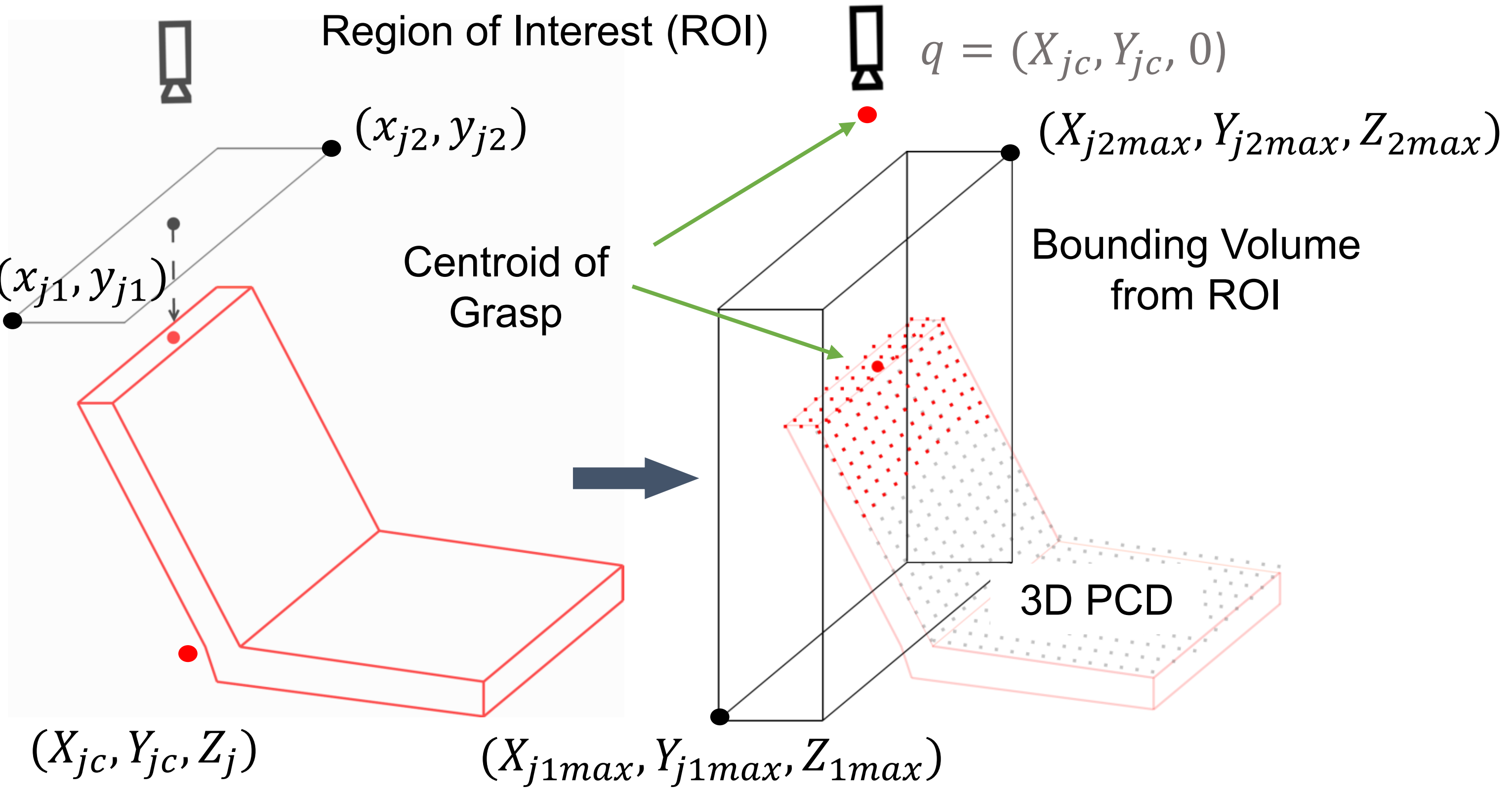
$$[X_j, Y_j] = \left[(x_j - c_x) \times \frac{Z_j}{f_x}, (y_j - c_y) \times \frac{Z_j}{f_y}\right]$$

$Z_j = \text{depth}\left(x_{jc}, y_{jc}\right)$ if $\left(x_{jc}, y_{jc}\right)$ exists

else $Z_j = \text{nominal depth}$

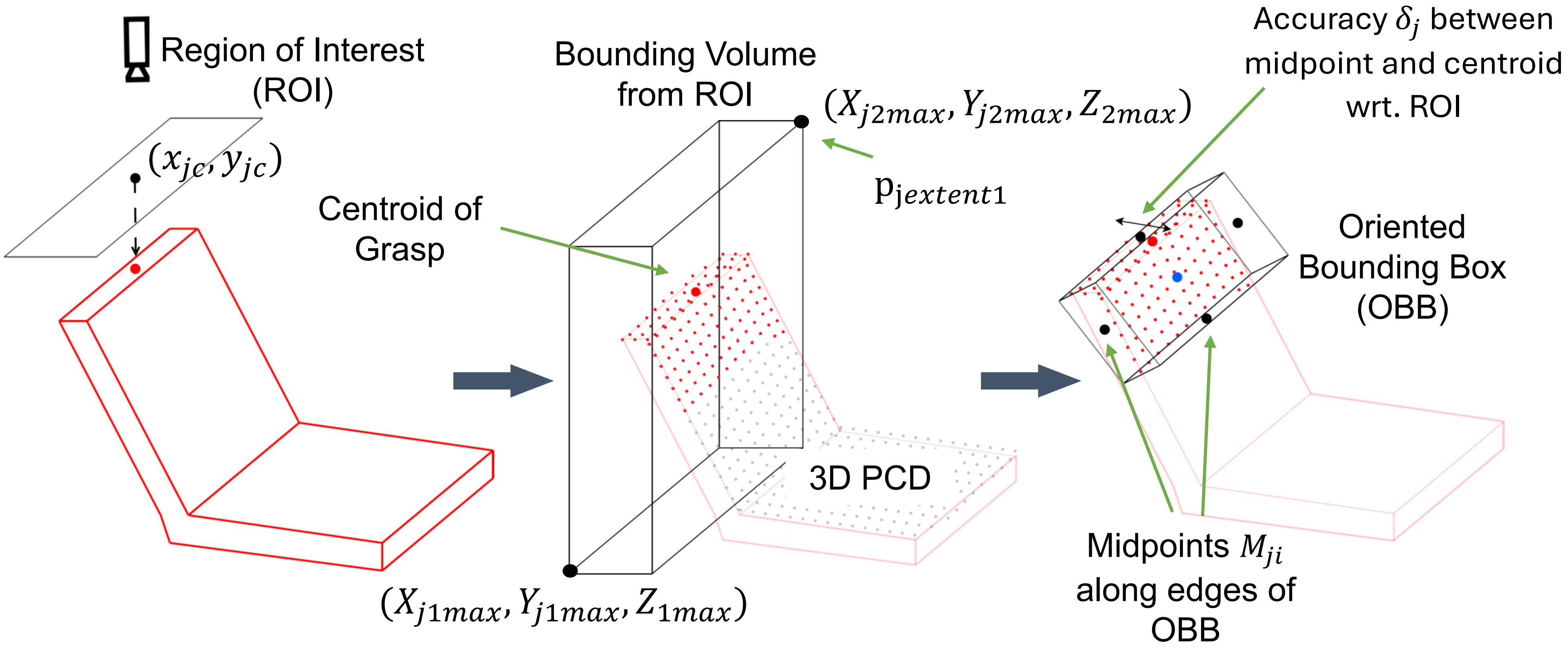
camera intrinsics: c_x, c_y, f_x, f_y

4. Point Cloud processing



$$B_{j\text{volume}} = \begin{cases} X_{j1_{min}} \leq X \leq X_{j2max}, \\ Y_{j1min} \leq Y \leq Y_{j2max}, \\ Z_{1min} \leq Z \leq Z_{2max}. \end{cases}$$

4. Point Cloud processing



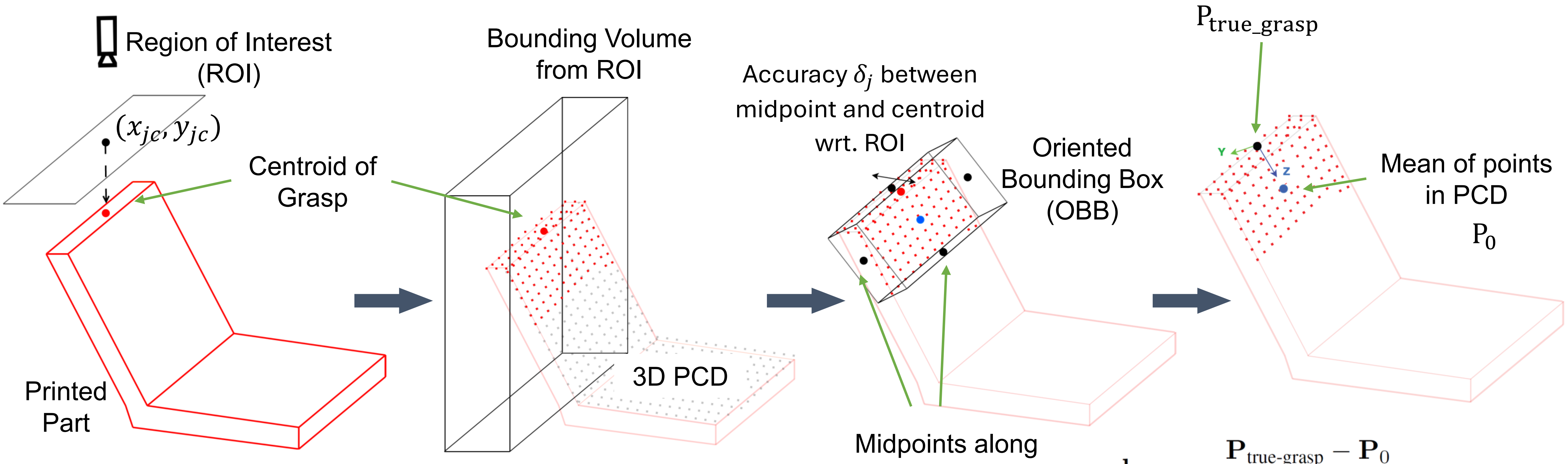
$$P_{jc} = (X_{jc}, Y_{jc}, Z_{jc})$$

$$\delta_j = \left| \frac{d_{max} - d_M}{d_{max}} \right|$$

where
$$d_{max} = \text{argmax}_{extent} \left\| p_{jextent} - P_{jc} \right\|$$
$$d_M = \text{argmin}_i \left\| M_{ji} - P_{jc} \right\|$$

Breakdown of Methodology and Algorithm: PCD

4. Point Cloud processing



$$\mathbf{d}_{\text{norm}} = \frac{\mathbf{P}_{\text{true-grasp}} - \mathbf{P}_0}{\|\mathbf{P}_{\text{true-grasp}} - \mathbf{P}_0\|}$$

if $\delta_j \leq$ threshold,

$$P_{true\_grasp} = P_{jc}$$

$$\mathbf{r}_3 = \mathbf{d}_{\text{norm}}$$

$$\mathbf{r}_1 = \frac{\mathbf{z} \times \mathbf{d}_{\text{norm}}}{\|\mathbf{z} \times \mathbf{d}_{\text{norm}}\|}$$

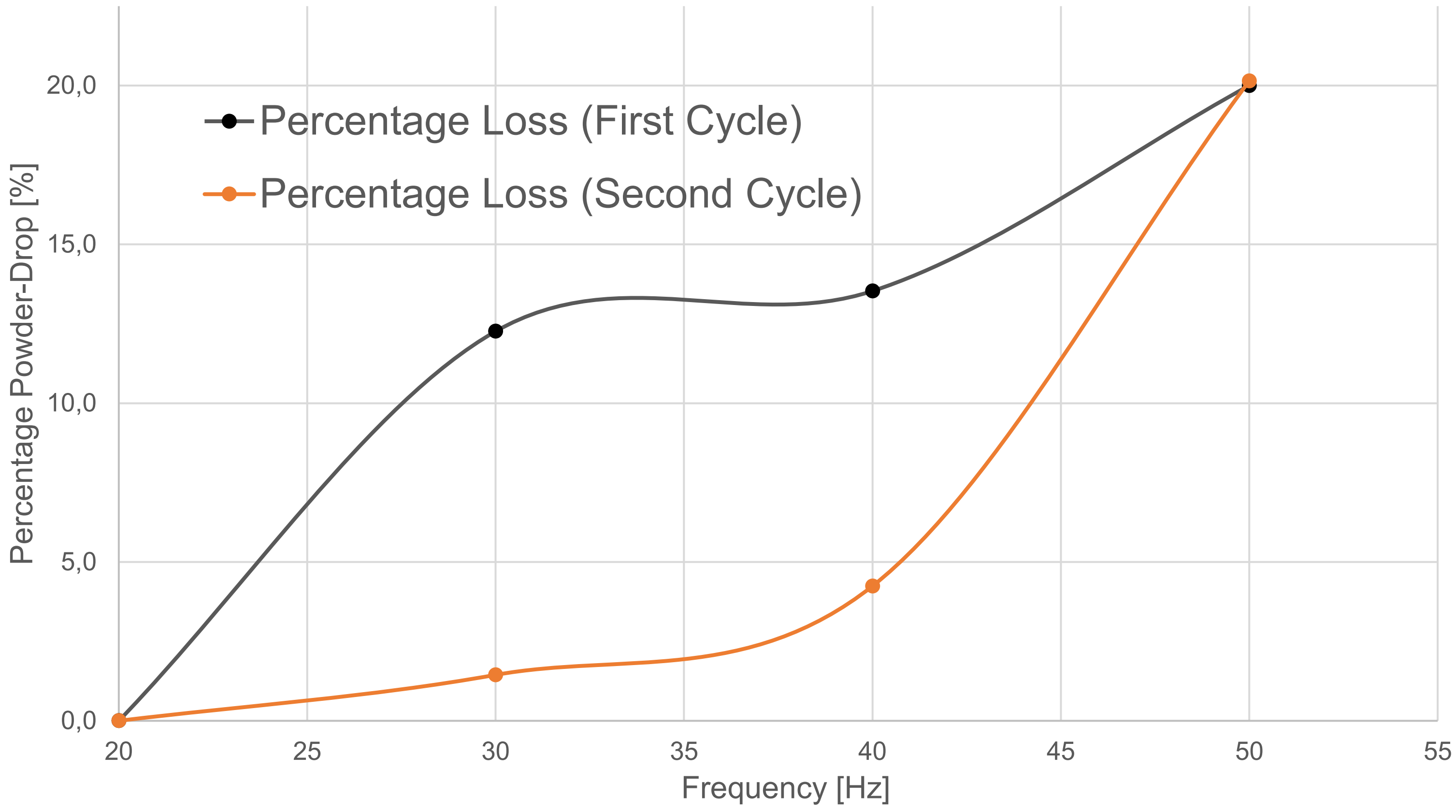
where $\mathbf{z} = [0, 0, 1]$

$$\mathbf{r}_2 = \mathbf{r}_3 \times \mathbf{r}_1$$

Results

Powder Removal with Vibrating Plate:

- Frequencies starting from 20 to 50 Hz were tested for 10 seconds.
- The frequencies were repeated over two cycles.



Powder drop represented by change in part mass through different frequencies

Results

Graspable edge detection:

- From the AI CNN training and the 60 tests conducted with the two validation parts.

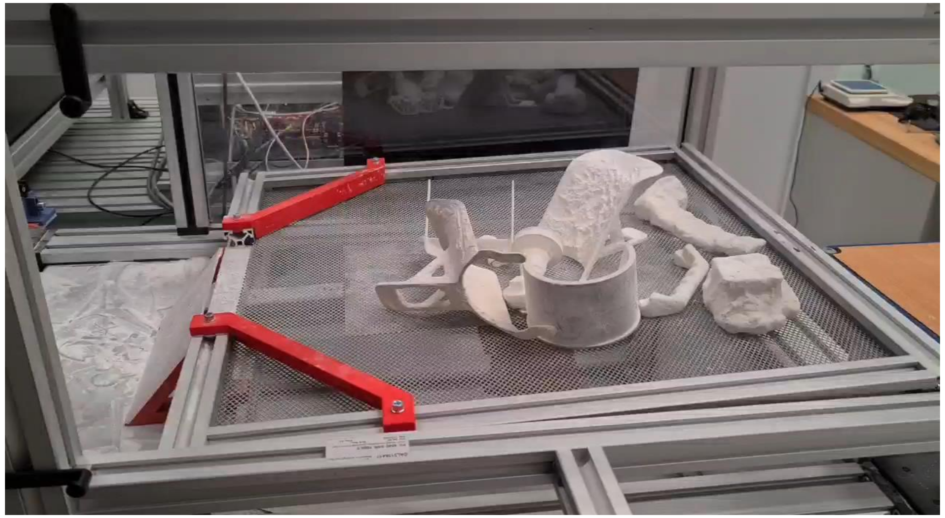
Success rates:

Parameter	Value
YOLO AI model Final Loss	0.71 (Cross-Entropy Loss)
Accuracy of 4 DoF Grasp Region (From CNN)	68.3 %
Accuracy of 6 DoF Graspable Edge (Singular parts)	92.5 %
Overall Accuracy (in cluttered environments)	63.2 %

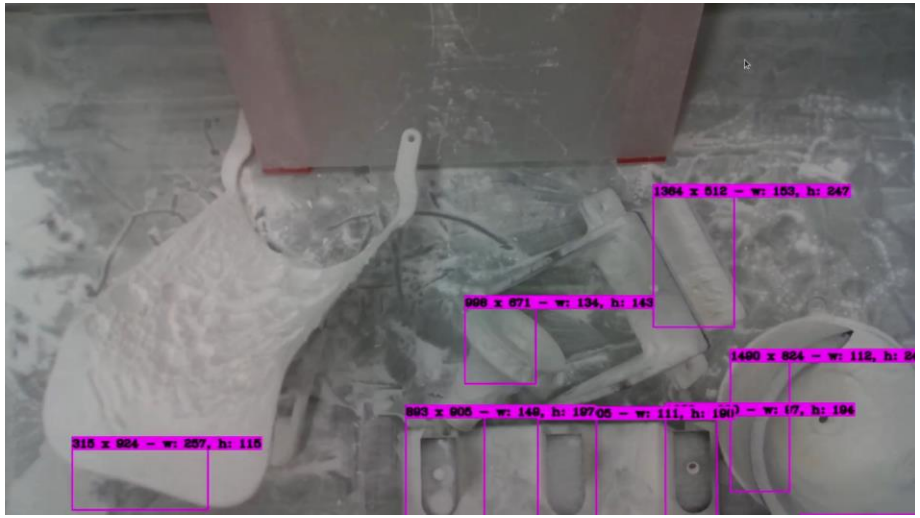
Notes:

- These do not include the grasping motion but the determination of a grasp point by itself.
- The experiment setup included both cluttered environments and single parts.
- Parts singled before picking had higher success rates.

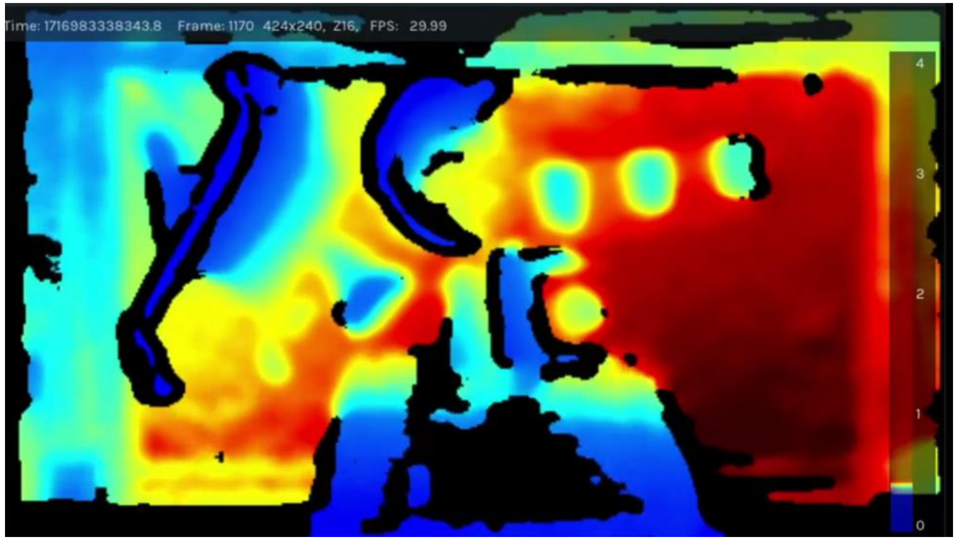
Video Demonstrations



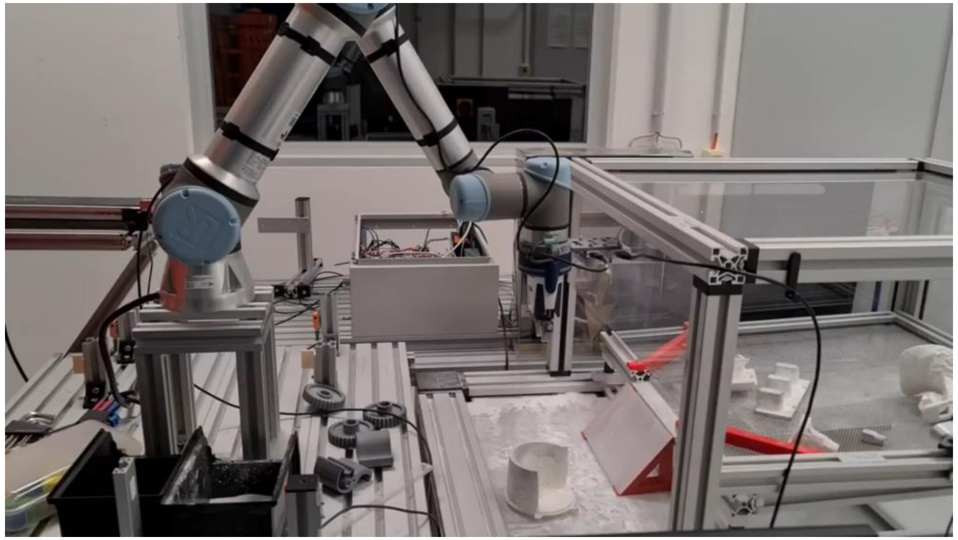
Video 1: Vibrating Plate at different frequencies



Video 2: Extraction of edge region in video



Video 3: 3D depth data



Video 4: Coordinates in Robot Frame for grasping

Conclusions

- Powder removal through vibrating plate:
  - 20 – 30 Hz: to remove bulk unprocessed powder.
  - 40 – 50 Hz: repeated cycles to remove caked unprocessed powder.
- Region proposal with YOLOv4/v7 for powder-covered parts successful with singular parts.
- Success rate drops by 30% in cluttered environments.
- Determination of a graspable edge with region proposal from CNN and PCD with 92.5% success rate.

Further Works:

- Use of larger variety of powder printed parts geometries to test powder removal.
- Mechanism to arrange parts in a single line before picking.
- Modification of the YOLO NN model, specifically for training of powdered-parts in cluttered environments.

Algorithm and dataset

The algorithm and dataset/NN model are available on our github:

- 500 images of the powder printed parts.
- Extended dataset with PCD can be made shared on request.

github: https://github.com/thd-research/edge-grasp-pose-detection

References

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[2] H. Nguyen, N. Adrian, J. L. Xin Yan, J. M. Salfity, W. Allen, and Q.-C. Pham, “Development of a robotic system for automated decaking of 3d-printed parts,” in 2020 IEEE International Conference on Robotics and Automation (ICRA), 2020, pp. 8202–8208.

[3] A. Mousavian, C. Eppner, and D. Fox, “6-dof graspnet: Variational grasp generation for object manipulation,” in 2019 IEEE/CVF International Conference on Computer Vision (ICCV), 2019, pp. 2901–2910.

[4] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You only look once: Unified, real-time object detection,” 2015.

[5] A. Herzog, P. Pastor, M. Kalakrishnan, L. Righetti, J. Bohg, T. Asfour, and S. Schaal, “Learning of grasp selection based on shape-templates,” Auton. Robots, vol. 36, no. 1-2, pp. 51–65, Jan. 2014.

[6] C.-Y. Wang, A. Bochkovskiy, and H.-Y. M. Liao, “YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors,” 2022.

Thank you very much for your attention!

Questions?

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