WORKSHOP:

Good Data for Agile Production, Logistics and Lab Automation

14 – 16 MARCH
Odense • Denmark
ERF2023

EUROPEAN ROBOTICS FORUM

eu ROBOTICS

10th anniversary
FOUNDED SEPTEMBER 2012

Agenda

GOOD DATA FOR AGILE PRODUCTION, LOGISTICS AND LAB AUTOMATION

11:05 **Introduction and Definition of Statements/ Key Questions**
Dr. Michael Suppa, Roboception GmbH

11:15 **Towards Detecting and Grasping Transparent Objects**
Prof. Markus Vincze, TU Vienna, Austria

11:25 **Robotic pick & pack: the Ocado Technology way**
Dr. Radhika Gudipati, Ocado Technologies, UK

11:35 **Data Generation for Lab Automation**
Dr. Patrick Courtney, Tec-connection, UK

11:45 **Good Data for Pick-and-Place in Agile Production**
Dr. Michael Suppa, Roboception GmbH, Germany

11:55 **Interactive Session/ Round Table Discussion**

12:20 **Conclusion and Take Home Messages**

Perception is the Key Technology for Flexible Automation

- In flexible automation, robots must be able to reliably detect and locate work pieces and human collaborators und varying illumination, work pieces type and locations
- In **logistics**, manual work is still pre-dominant due to the complexity of tasks and the variation of objects.
- In **industrial automation**, accurate placement is usually the key challenge
- In **lab automation,** usually fragile and transparent objects must be handled in the processes including human interaction
- Individual engineering of solutions is costly and does not scale

How to Scale Vision for Grasping in Robotics

FLEXIBILITY IS KEY

Industrial Automation

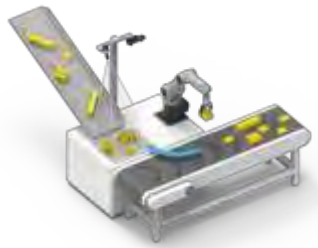
- Classical approach to use mechanical fixtures
- Individual engineering for feeding and grasping
- Usually <100 different parts
- Model data available
- Pick-and-place

Vision System

- Removal of fixtures for flexible cell design
- Model-driven approaches require a model but allow for time-saving off-site training
- Combination with classical methods allows for accuracy and robustness

Logistics

- High cycle time with 1.000 picks/h
- Usually >1.000 parts
- Objects unknown
- Pick-and-drop



Vision System

- Enables application of robots in the domain
- Data-driven approaches require data, i.e. time-consuming on-site recording and training
- Introduction of model-driven approaches reduces greediness

Lab Automation

- Traceability of process and documentation
- Transparent objects
- Pick-and-place

Vision System

- Enables application of robots in the domain
- Model-driven approaches with synthesized data for e.g. transparent objects

Good Data, not Big Data

SIMULATION REDUCES THE DATA GREEDINESS

Andrew Ng states that

"80% of the AI developer's time is spent on data preparation",

and calls for **GOOD DATA**, i.e.

"Data that is defined consistently, covers the important cases, has timely feedback from production data, and is sized appropriately."

https://www.forbes.com/sites/gilpress/2021/06/16/andrew-ng-launches-a-campaign-for-data-centric-ai

DEPALLETIZING

SINGULATION

BIN PICKING

- Development of model- and data driven software products for picking known and unknown items in mixed scenarios
- Data recording and labelling effort vs. integration time onsite
- Assessment of ground truth exact placement
- Working with partially and/or unknown objects
- Amount of real data in relation to synthetized data

TECHNISCHE UNIVERSITÄT WIEN
Vienna | Austria

AUTOMATION & CONTROL INSTITUTE
INSTITUT FÜR AUTOMATISIERUNGS- & REGELUNGSTECHNIK

Towards Detecting and Grasping Transparent Objects

Markus Vincze

TU Wien, Automation and Control Institute

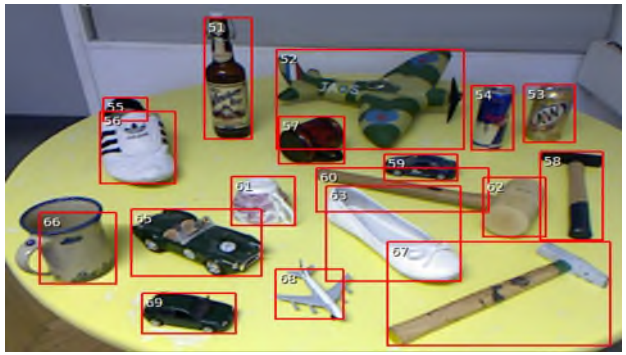
vincze@acin.tuwien.ac.at

ERF 15.3.2023, WS „Good data for agile production, logistics, and lab automation"

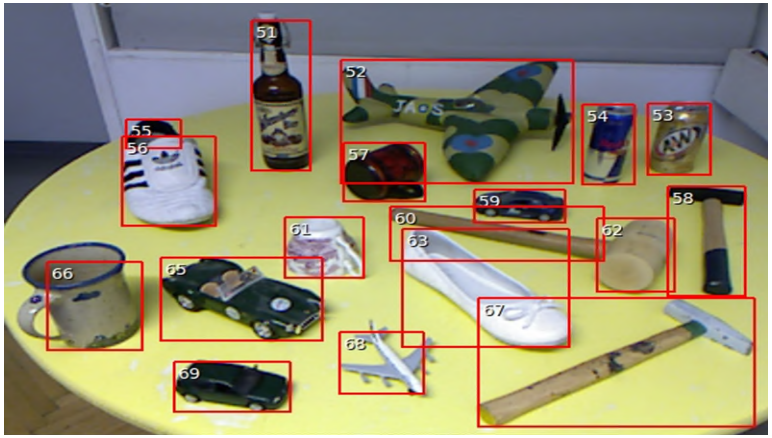
V4R – Vision for Robotics

„We make robots see“

- Objects X
  - Modelling
  - Recognition
  - Classification
  - Pose estimation
  - Manipulation
- RGB(D) images



Transparent Objects



Verification of Object Pose

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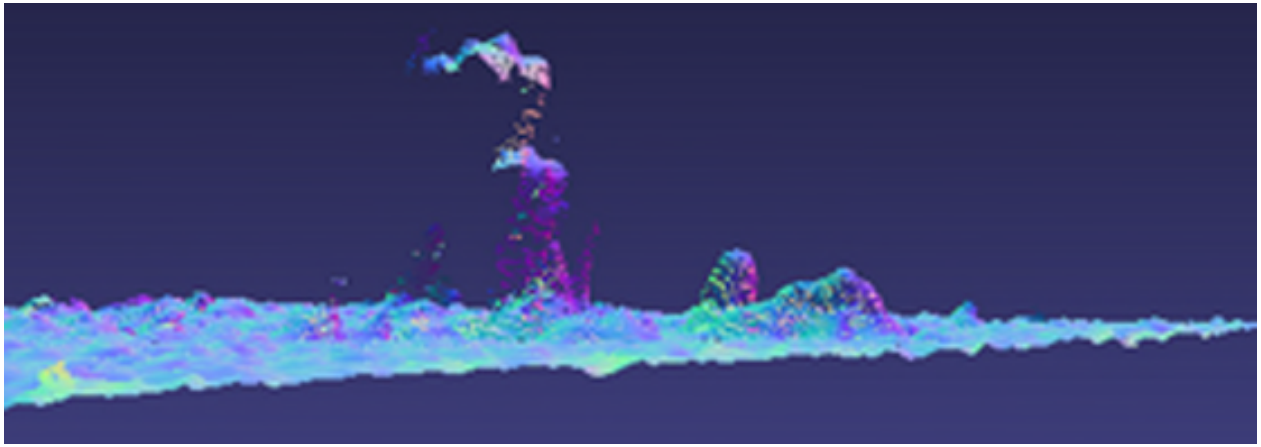
Traceable Robotic Handling of Sterile Medical Products

- Verification of every assembly step and creation of an Audit trail
- Recognition of transparent and small parts

Partner:
Tecnalia,
invite,
CEA,
UoB,
astech,
Biolago

Transparency: Challenges

- Missing depth data
- All visible in RGB data

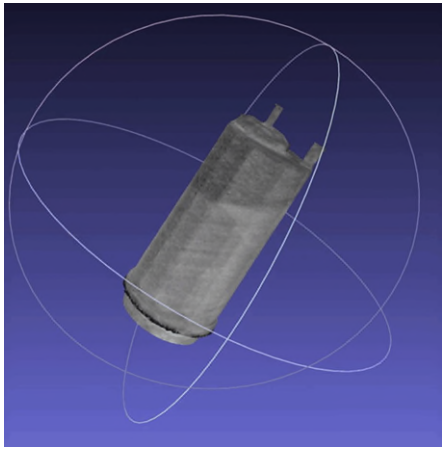


Approach

- Tools for creating data
- Modelling/rendering transparent objects
- Object pose estimation and verification
- Integration on robot for object grasping

Creating a Dataset

Recording sequence



3D model from coated transparent objects

- Marker and calibrated KUKA arm for accurate camera pose
  - RealSense D415, D435, automatic motion planning
- Accurate models from scans using Photoneo sensor
- Scan with up to 104 views per scene

Good Data: Groundtruth?

Do you really trust GT?

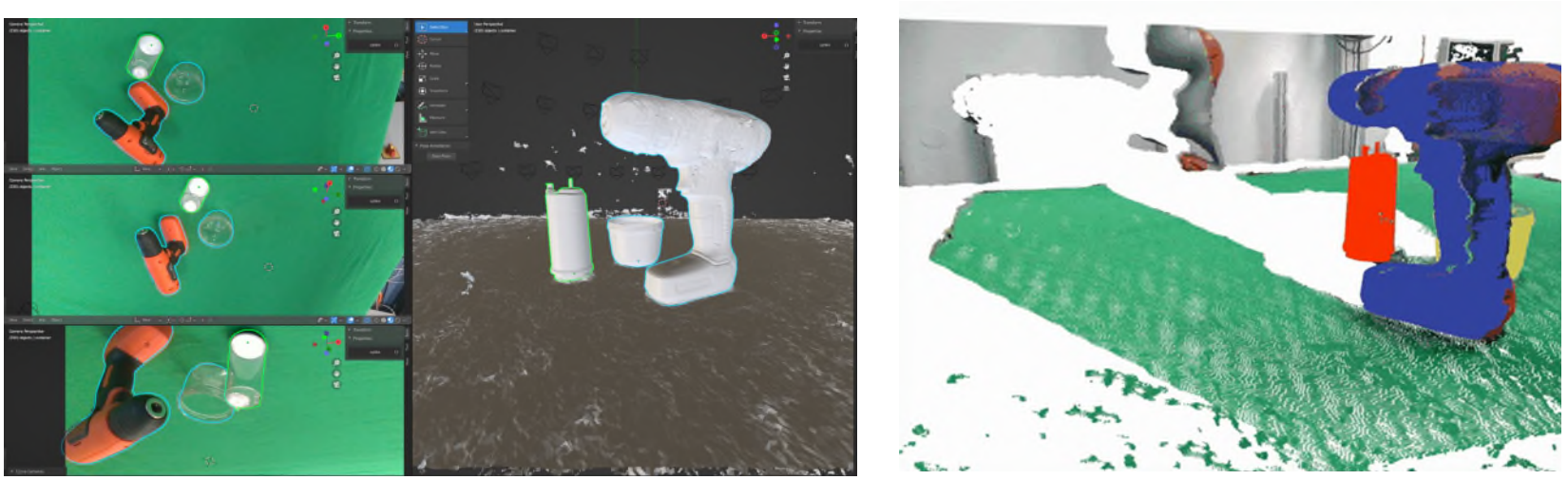
Nets learn what is annotated

- To get published, improve evaluation by an epsilon
- Tune architecture & parameters?

Solve the actual challenge!

- Good data!
- Tricky objects
  - Transparent, small, shiny, …
  - Similar objects classes (LienMOD)

3D-DAT – Annotation Tool



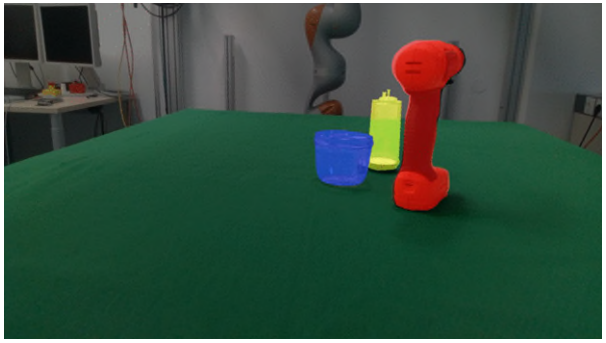
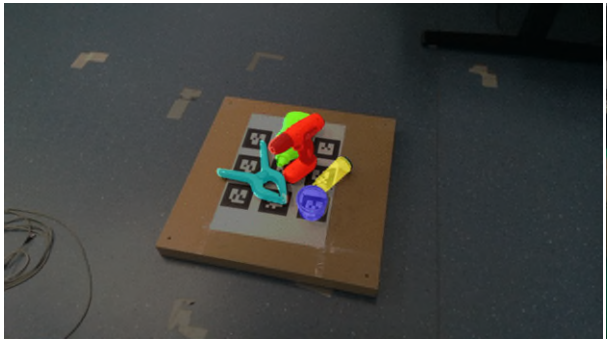
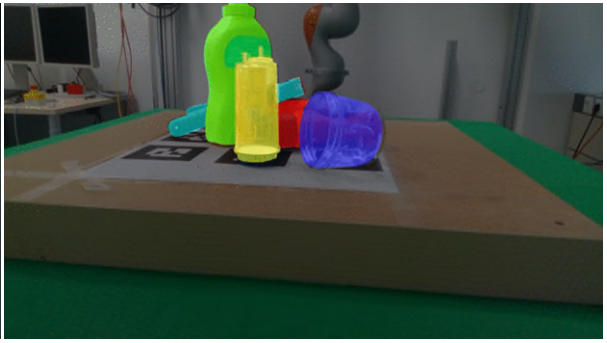
Pose annotation of tabeltop scene

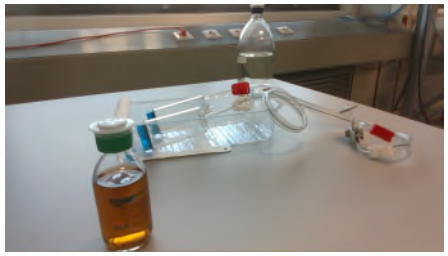
- Place one object with multiple views → transfer to other 103 views
- Automated NeRF reconstruction, modelling, and fit to data
  - Neural Rediance field – volume modelling
- Allows to place models with poor depth data (transparent objects)

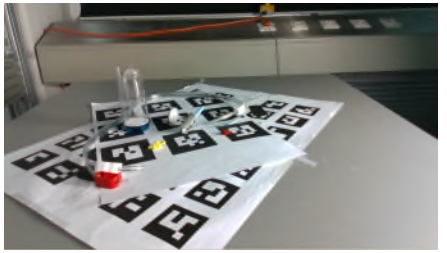
[Suchi et al., RA-L 2021, ICRA 2023]

Examples

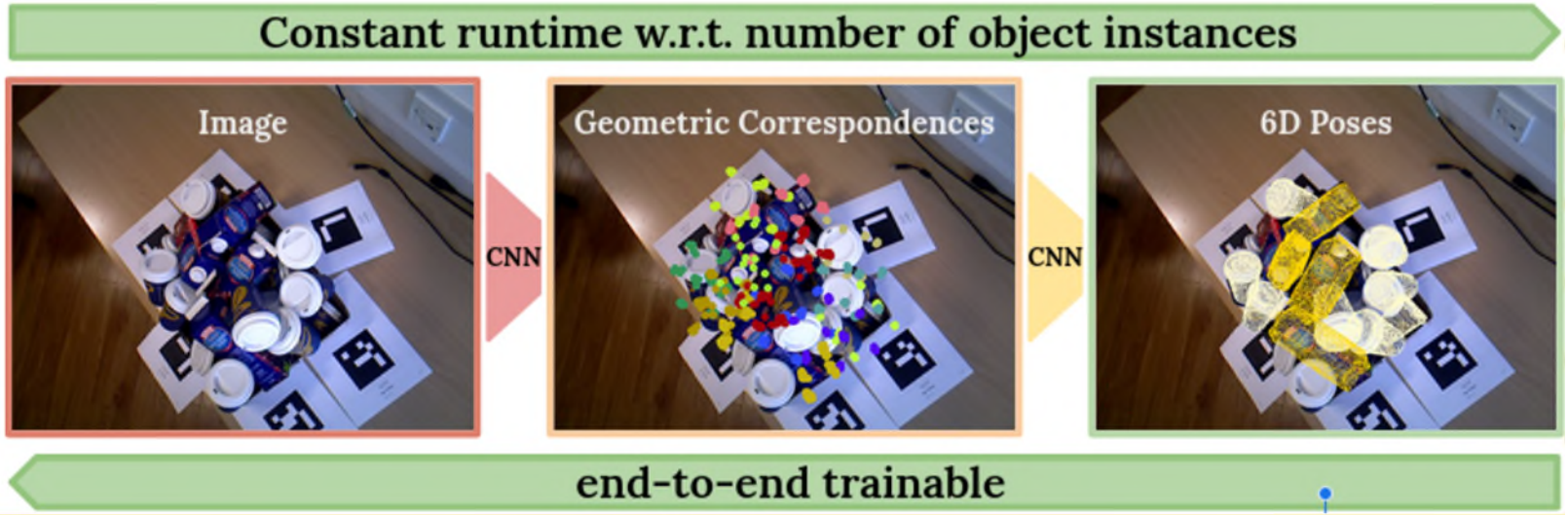






COPE End-to-end trainable Constant Runtime Object Pose Estimation



Learn from a lot of synthetic data plus a few samples

Calculating mutual IoU in RGB image

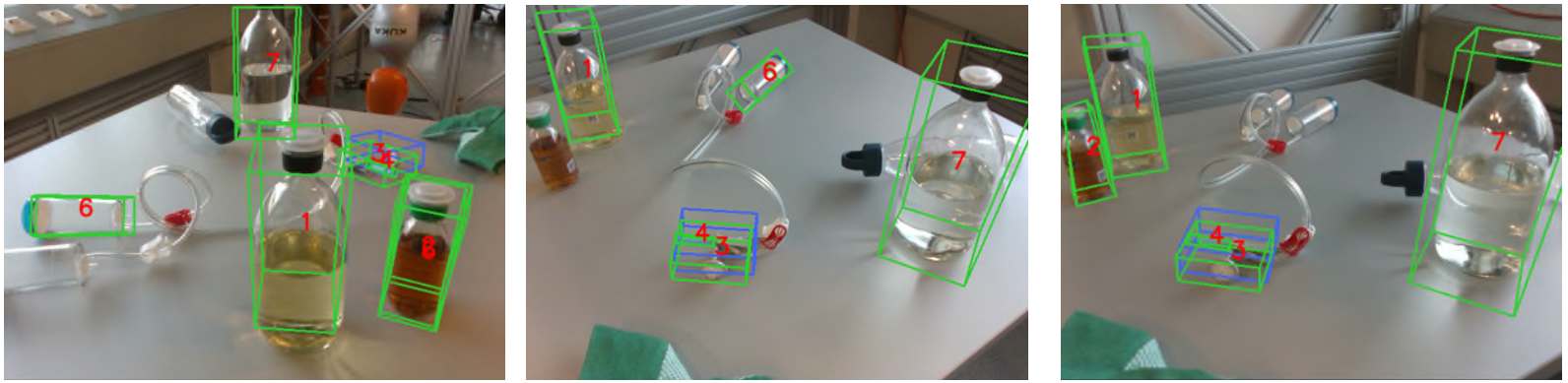
- Pose hypotheses are clustered →
- nearly constant runtime wrt. number of object instances

24 fps with 90 objects; LineMod 74%; LM-O: 35%

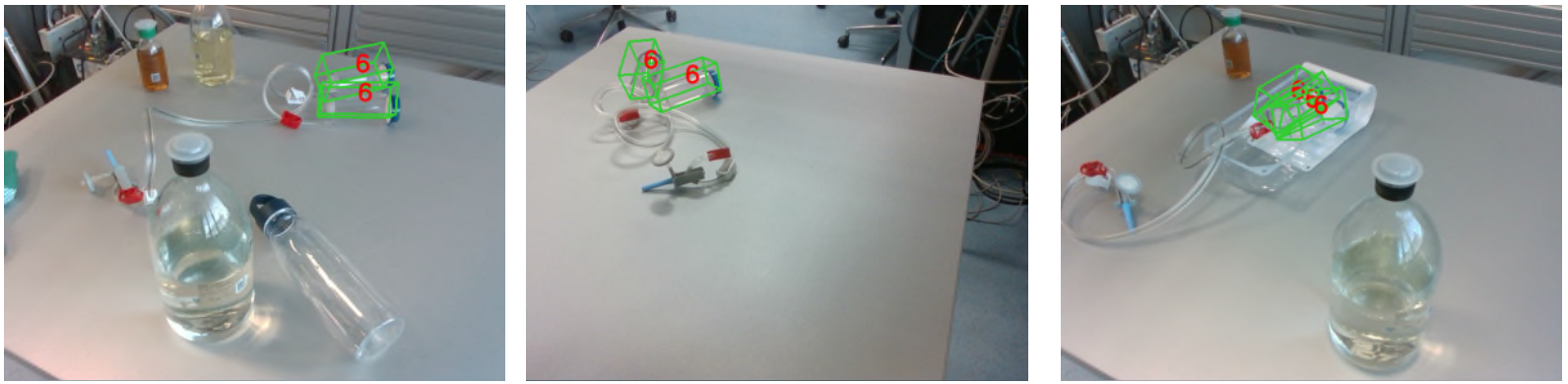
[Thalhammer et al.: COPE, WACV 2023]

COPE Results Transparent Objects

COPE – Synthetic data with random texture

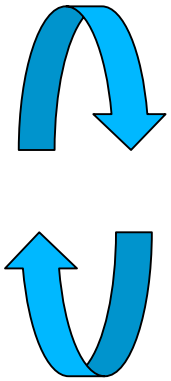


COPE – Real World Data and Synthetic data with random texture



Another problem of real data: sample bias

Verification Loop – Vision & Physics Simulation



Physics simulation to improve pose estimate

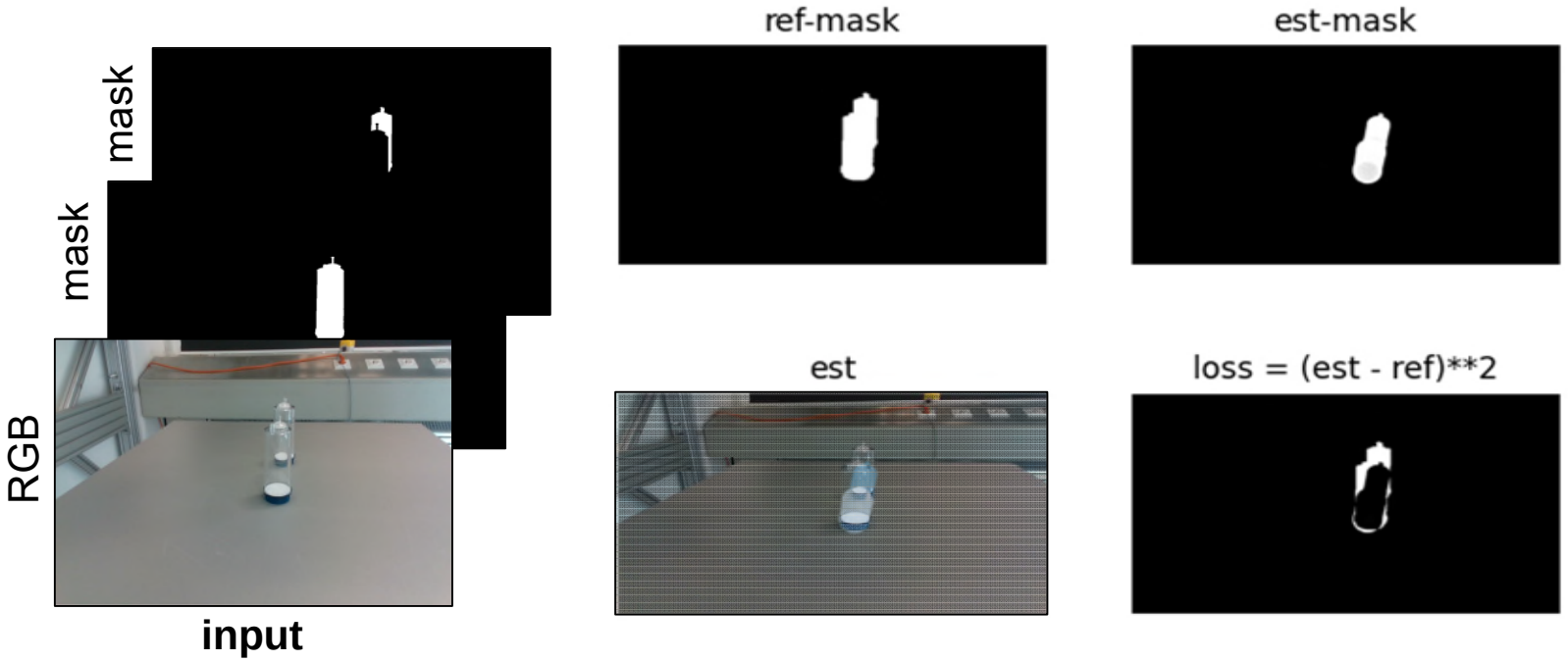
Pose refine through inverse rendering

Verification = hypothesis generation and plausibility check with physics simulation

Verification – Multiple Objects

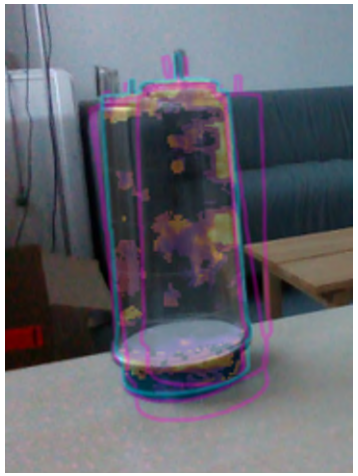
Extended inverse rendering pipeline

- **Multiple objects** in joint optimization
- **Collisions** as soft constraints



Conclusion

- Datasets need to capture actual challenge
- Synthetic data is sufficient if close to actual scenes
  - Methods show significant dependence on view point and type of scene
- One → ALL views: annotate one and transfer [3D-DAT, Suchi et al., ICRA 2023]
- Pose estimation gives a hypothesis
  → Verification of pose with
  vision & physics simulation loop



TRACEBOT
HORIZON 2020

Robotic pick & pack: the Ocado Technology way

Dr Radhika Gudipati

Sr Research Coordinator (Robotics & AI)

Who we are

Ocado Technology - technology pioneers

We’re solving some of the **toughest technological challenges** of our age

We bring together some of the greatest minds in engineering, product, data science, robotics and UX

Twelve development centres out of **eight countries**

Twelve global retailer partners

Over 500+ patents granted and counting...

2,500+ technologists

Our retail partners

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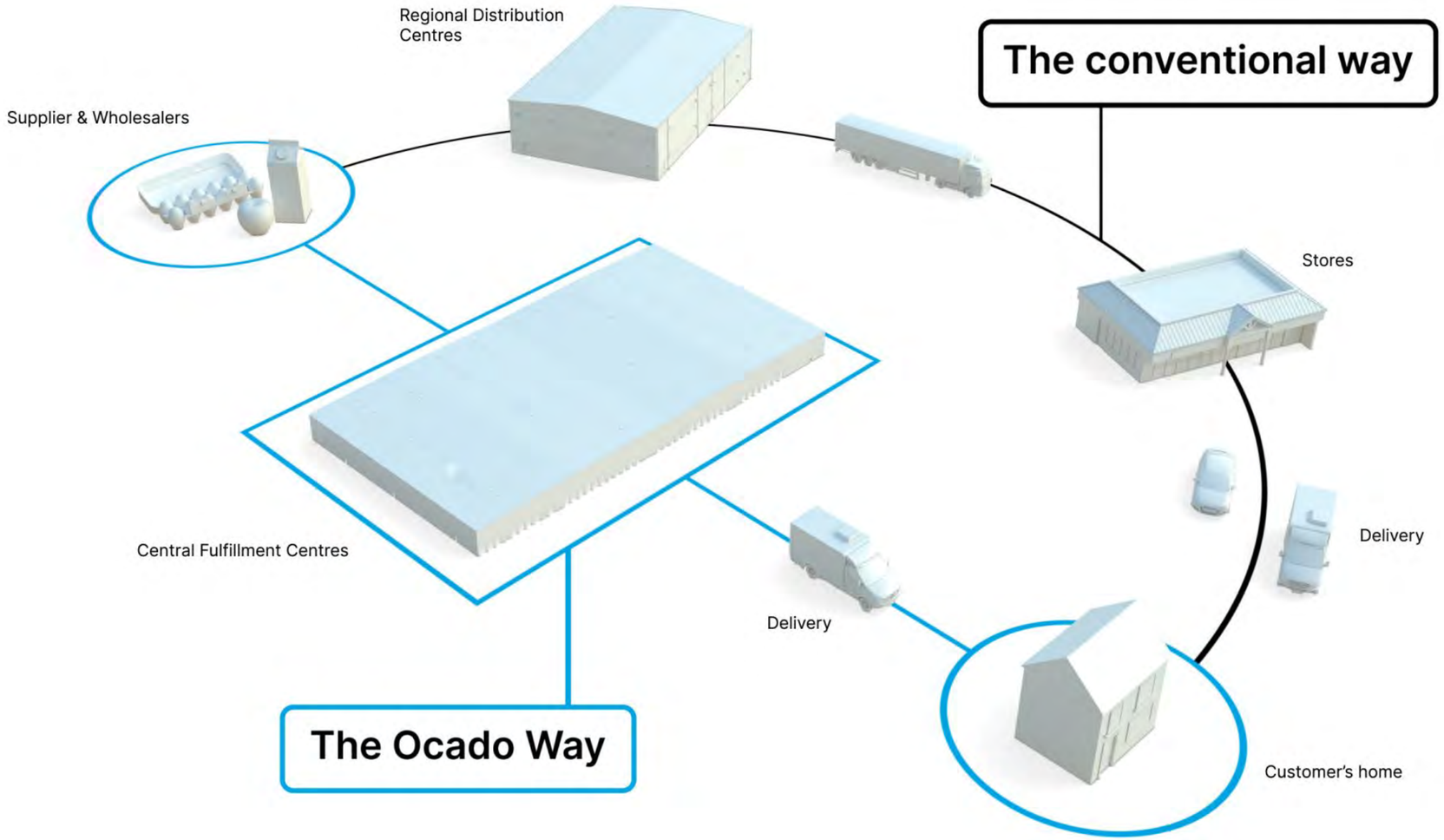
Our pioneering technology

The Ocado way



The Hive

What is The Hive?

- The Hive consists of the grid and the bots which run on it
- Thousands of bots are orchestrated by AI, collaborating to pick 50-item customer orders in just five minutes, and up to 150 orders simultaneously
- Storage of items in the grid is constantly optimised for availability and efficiency
- The Hive enables fast, accurate picking for the best economics in grocery fulfilment.

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Our bots

How our bots work:

- Bots whizz around the grid at speeds of up to 4m per second, with just millimetres between each one
- Bots operate as a highly coordinated swarm, orchestrated by our AI ‘air traffic’ control
- Bots are modular and identical - any requiring preventative maintenance can instantly be replaced with no loss of throughput
- Each bot records 1 GB of data per day, or 4TB per day for an entire swarm*
- We use ML to analyse this vast data information for monitoring and oversight.

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Robotic picking and packing

YouTube link:
https://www.youtube.com/watch?v=dvSOUCjMC8A

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Collaborative robotics

Robotic assistant: “Second hands”

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

Robot-human handover

University College London

Vision - object recognition

SAPIENZA UNIVERSITÀ DI ROMA

High level reasoning / planning state A to state B

Karlsruhe Institute of Technology

Robot hardware, low-level planning, natural language I/O

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System integration

SECOND HANDS

SecondHands Video gallery:
https://secondhands.eu/index.html@p=85.html

THANK YOU !

Any Questions ?

We're technology pioneers powering the future of online grocery and beyond

email: radhika.gudipati@ocado.com

Join us:

https://ocadotechnology.co/JoinUs

@OcadoTechnology

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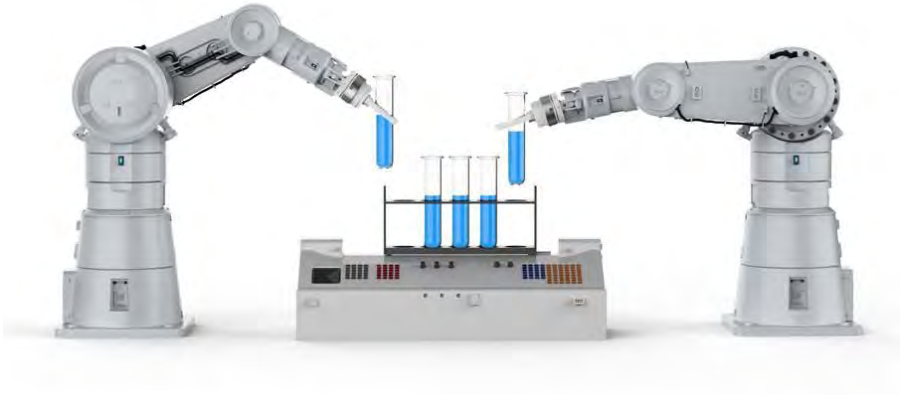
ERF 2023

Good data for agile production, logistics and lab automation

Patrick Courtney

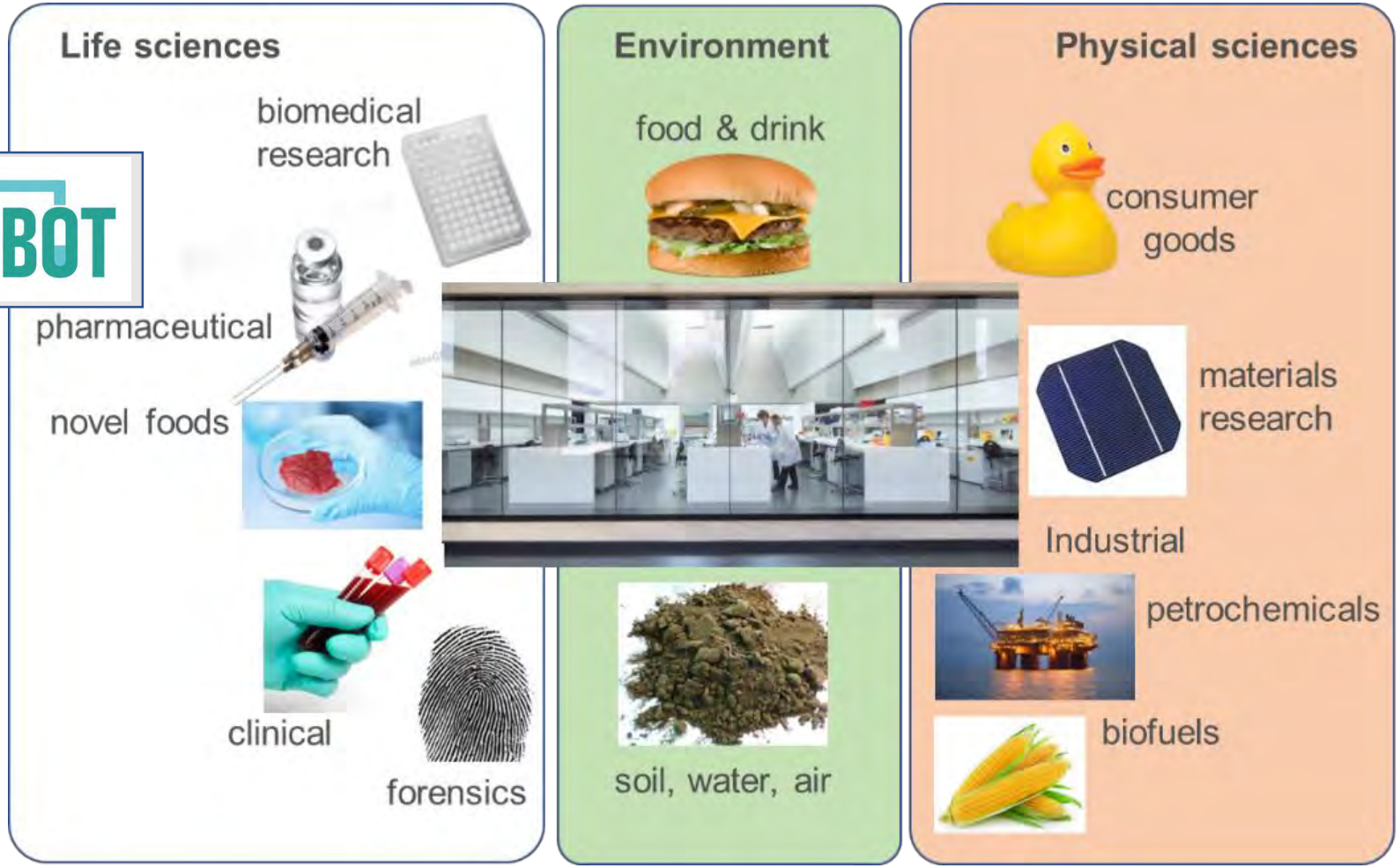
Date and Time: 15 March 2023, 11:05-12:25

TG analytical laboratory robotics



What is the lab and why is it important?

a typology of end-user laboratory



Three main capabilities

Data service
"What is this?"
(is it sick/safe/quality ok)

Product knowledge
"How do I make this?"
(prototyping)

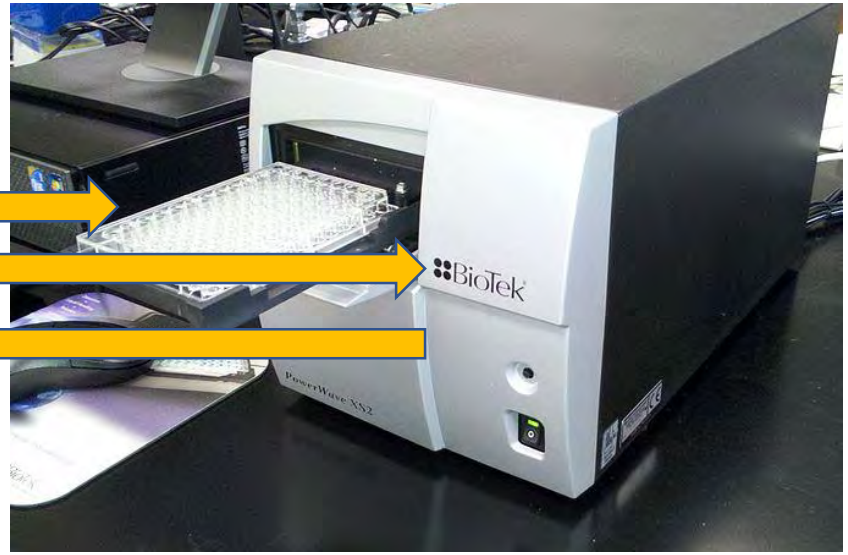
Process knowledge
"How can I make these well?"
(how to scaleup)

An increasing role for robots/automation/AI

Medicines value $1T, compare to automotive 100bn and electronic components and systems 600bn

Data generation within Lab Automation

- What data do we deal with?
  - Objects – samples and materials, in containers
  - Devices – move, measure, heat, stir….
  - Results (files, images)
  - Services – recipes (protocols)
  - Tasks - assembling, running, cleaning etc



https://commons.wikimedia.org/wiki/File:Microplate_reader.jpg

- How can we acquire (good) appearance data?
- Some initiatives, some gaps

SBS labplate format

perception and reality

Microtitre plates – role of standards, consumables

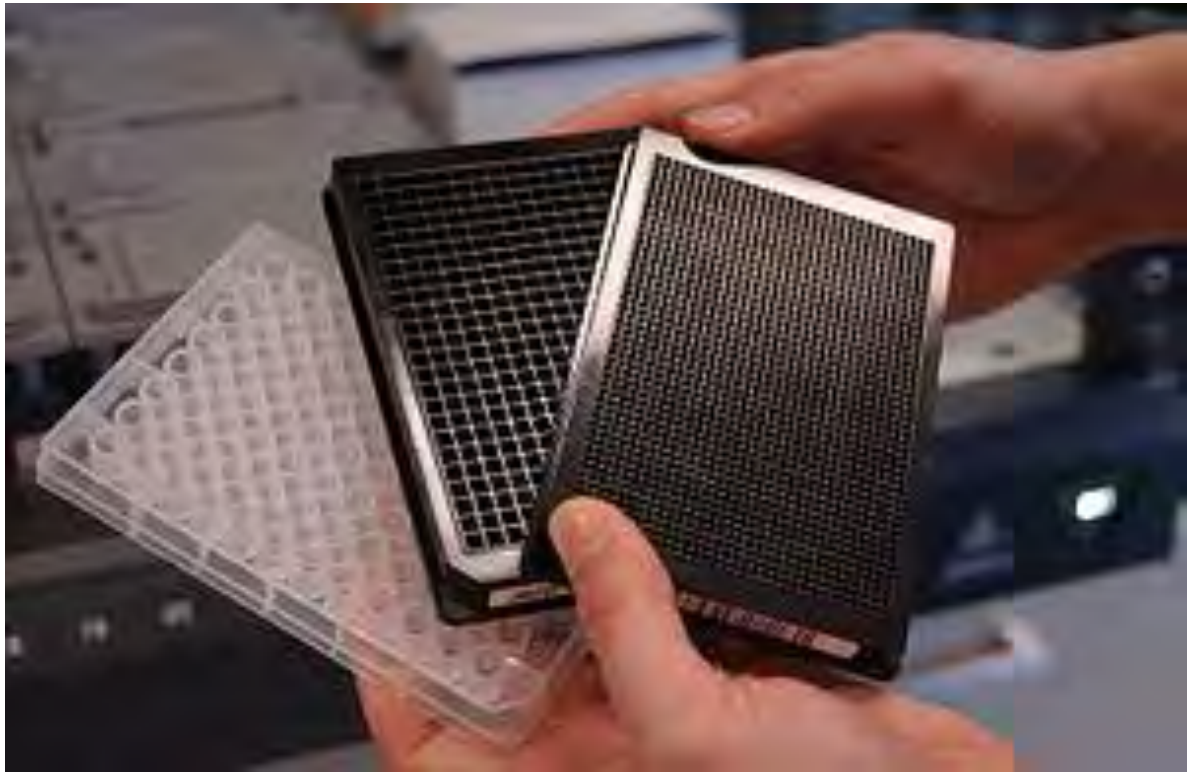
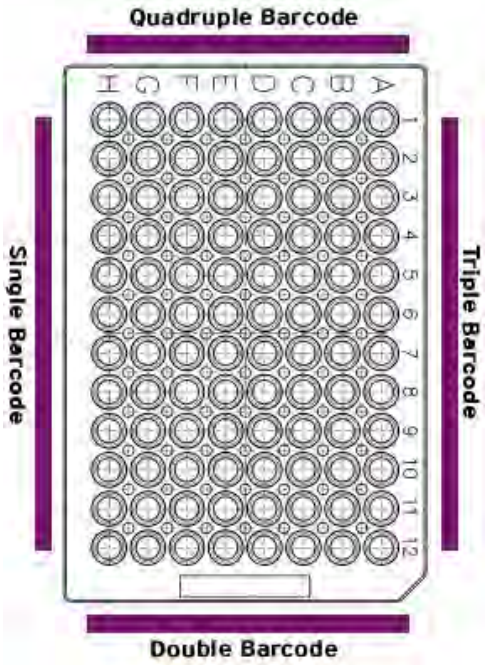
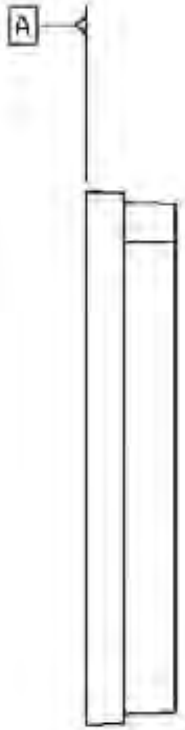


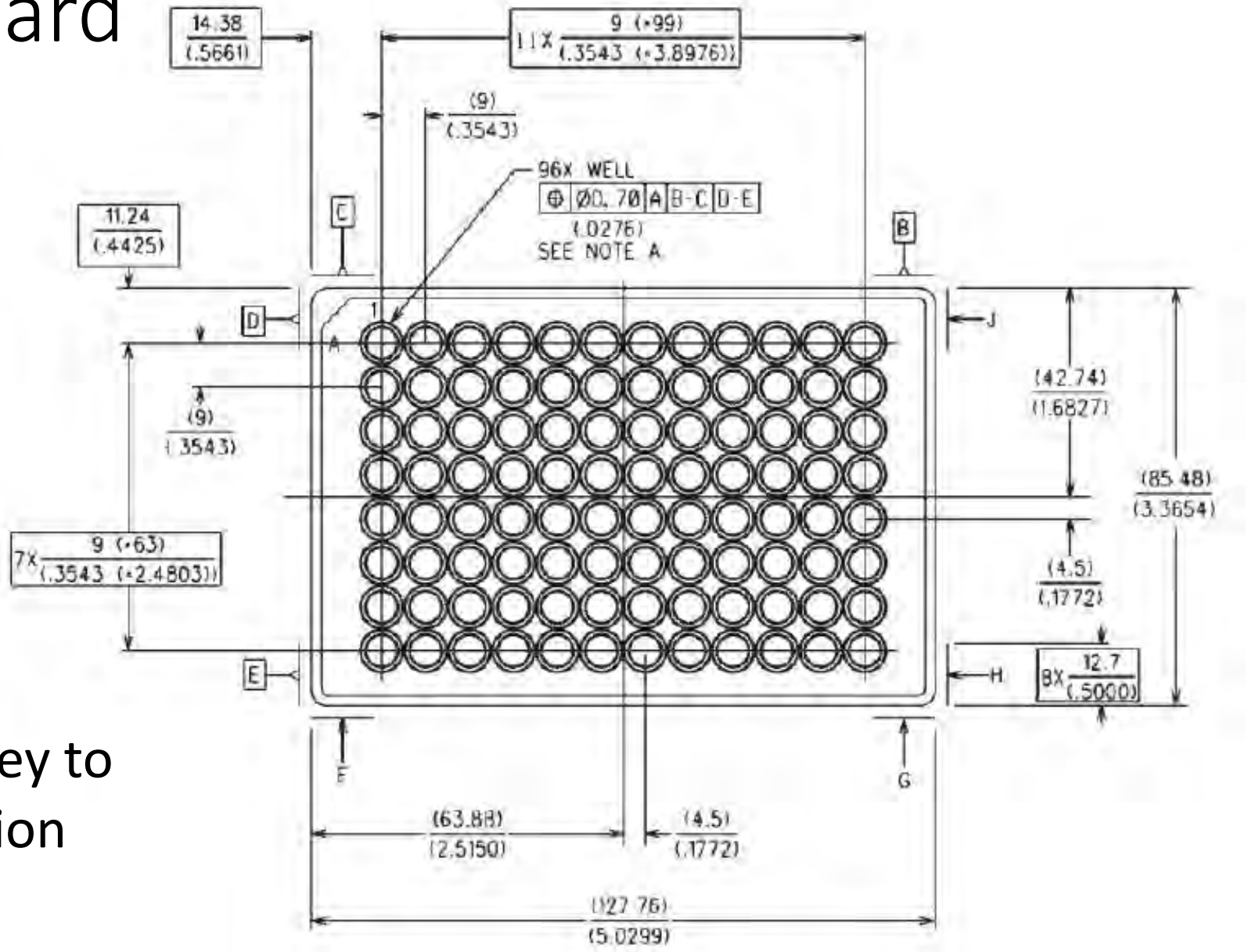
Image credit: SBS/SLAS, Hamilton

an ANSI standard

1996 to 2003







This has proved to be key to success of lab automation

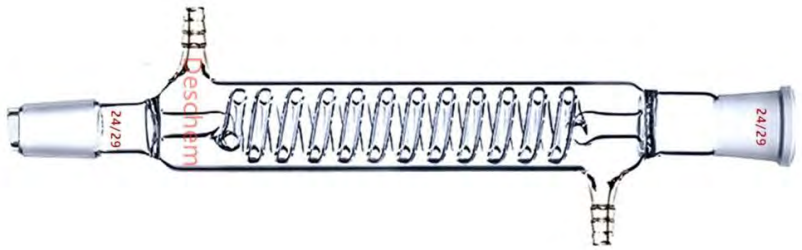
But still many gaps

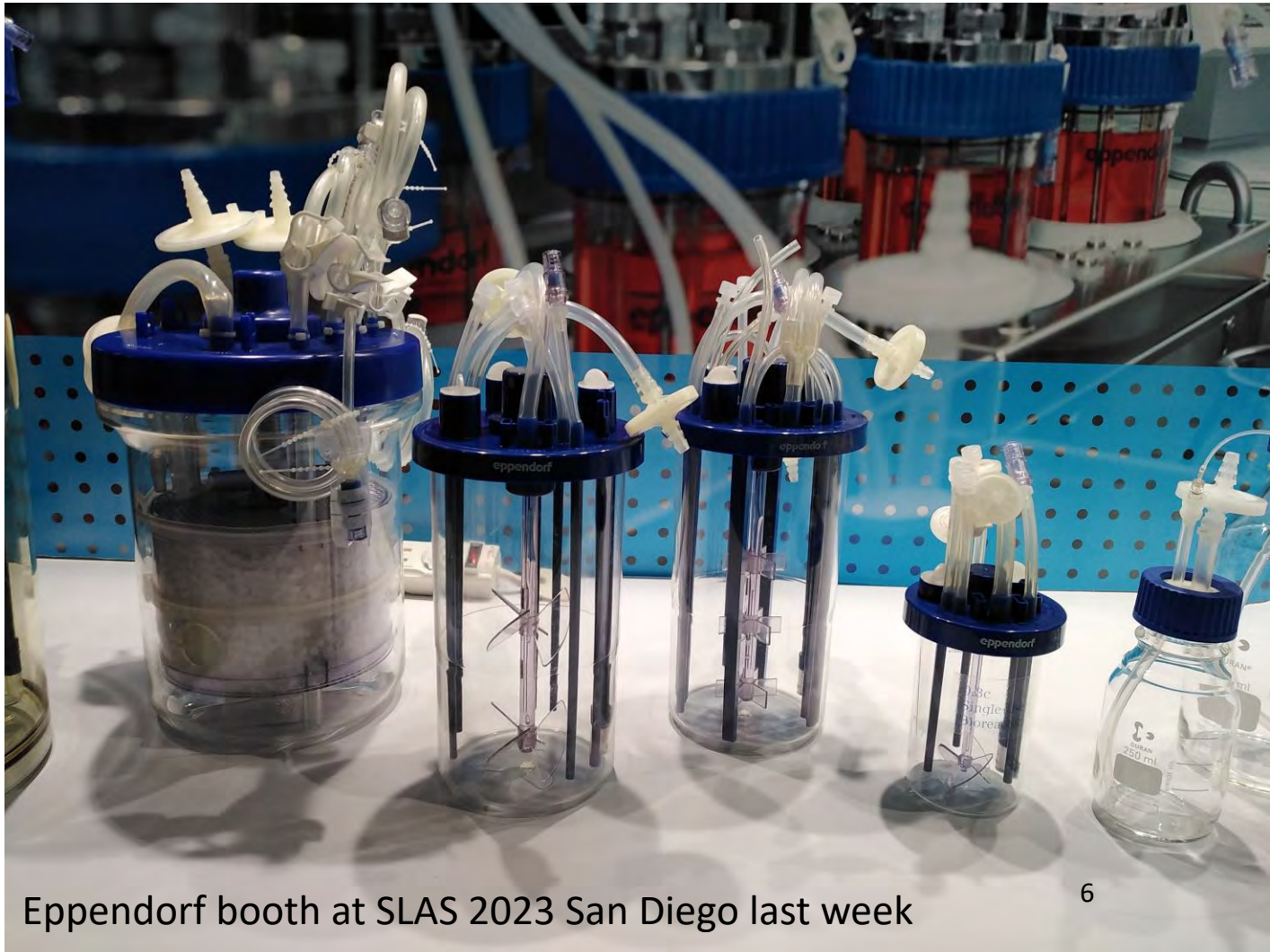
ANSI SLAS 4-2004 (R2012) *(formerly recognized as ANSI/SBS 4-2004)*

and still many new objects

- Increasing role of 3D printing with availabilty of CAD?

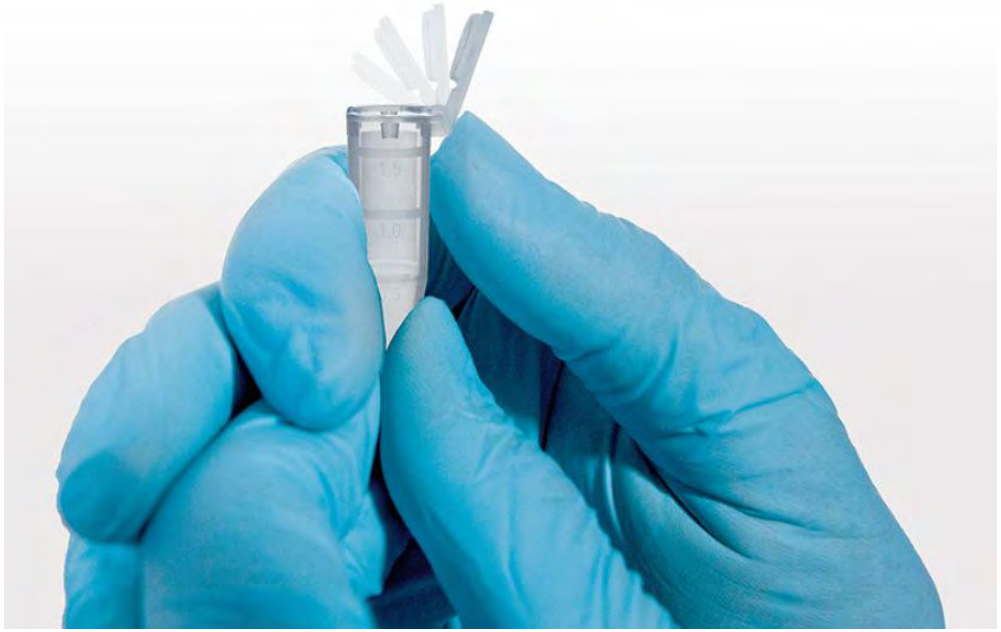
- A return to glass blowing? (no CAD)





Eppendorf booth at SLAS 2023 San Diego last week

These objects are getting more robot friendly



1.5 mL FlipTube facilitates handling without risk of aerosol

Azenta storage tubes

Still a challenging visual environment

Still a challenging visual environment

- New non-robot friendly lab design

Capturing recipes and tasks: some steps in this direction

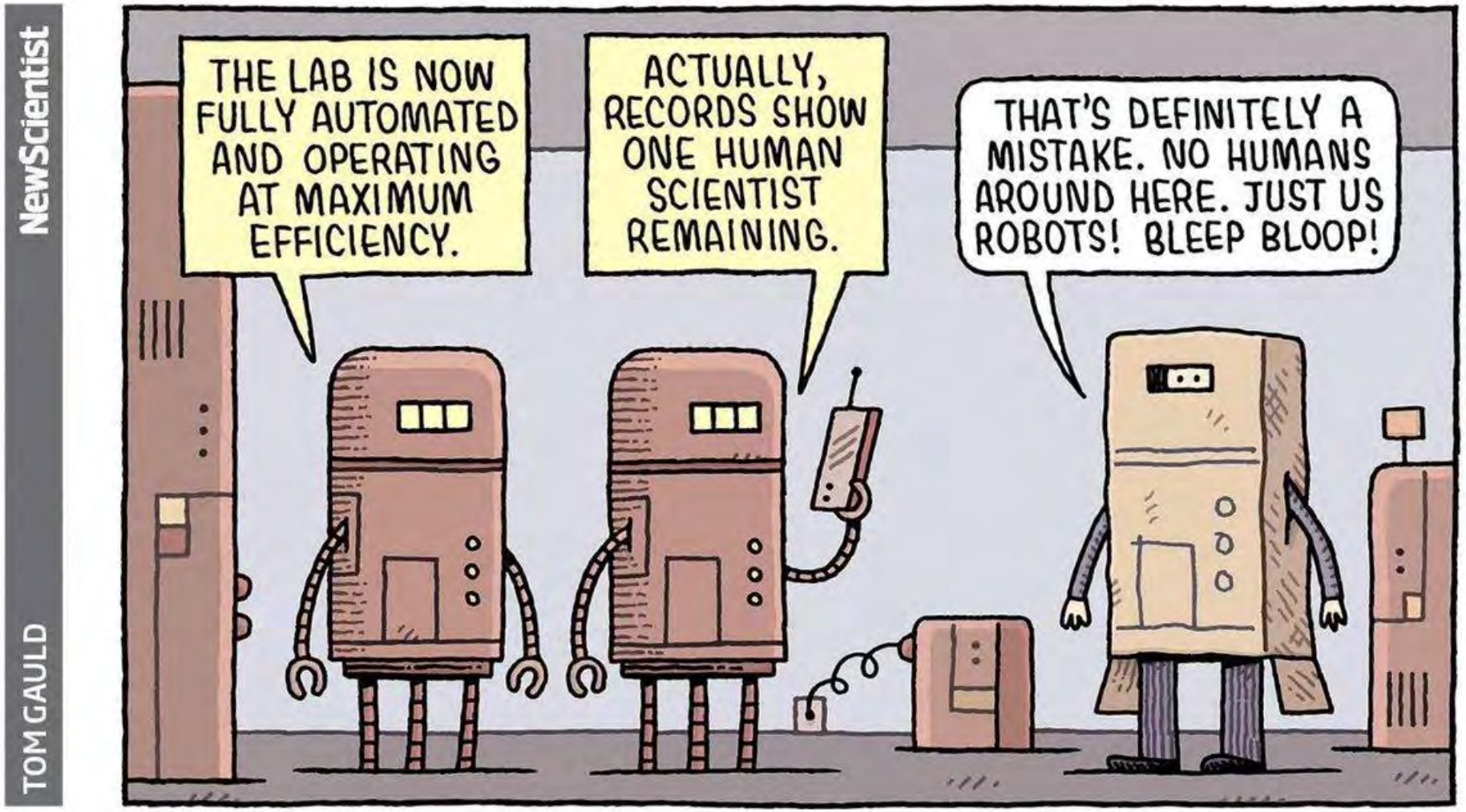
- Watching people in the lab

Fraunhofer IPA, CSEM, Klavins/U Washington…

Return to the questions set

- GOOD DATA, NOT BIG DATA: Synthetic data generation based on model data and enriched by real data create realistic ground-truth training data sets for machine learning.
- PLUG-AND-PRODUCE: The perception component of an automation solution must be easily adjustable to changing requirements.
- EASE-OF-USE: With robot vision expertise being a scarce resource, usability for robot users with little to now vision knowledge is a game-changer. These trends increase the flexibility making the RoI much easier to demonstrate, especially for SMEs.
- What else is missing: **a good ontology!**

Thanks for listening

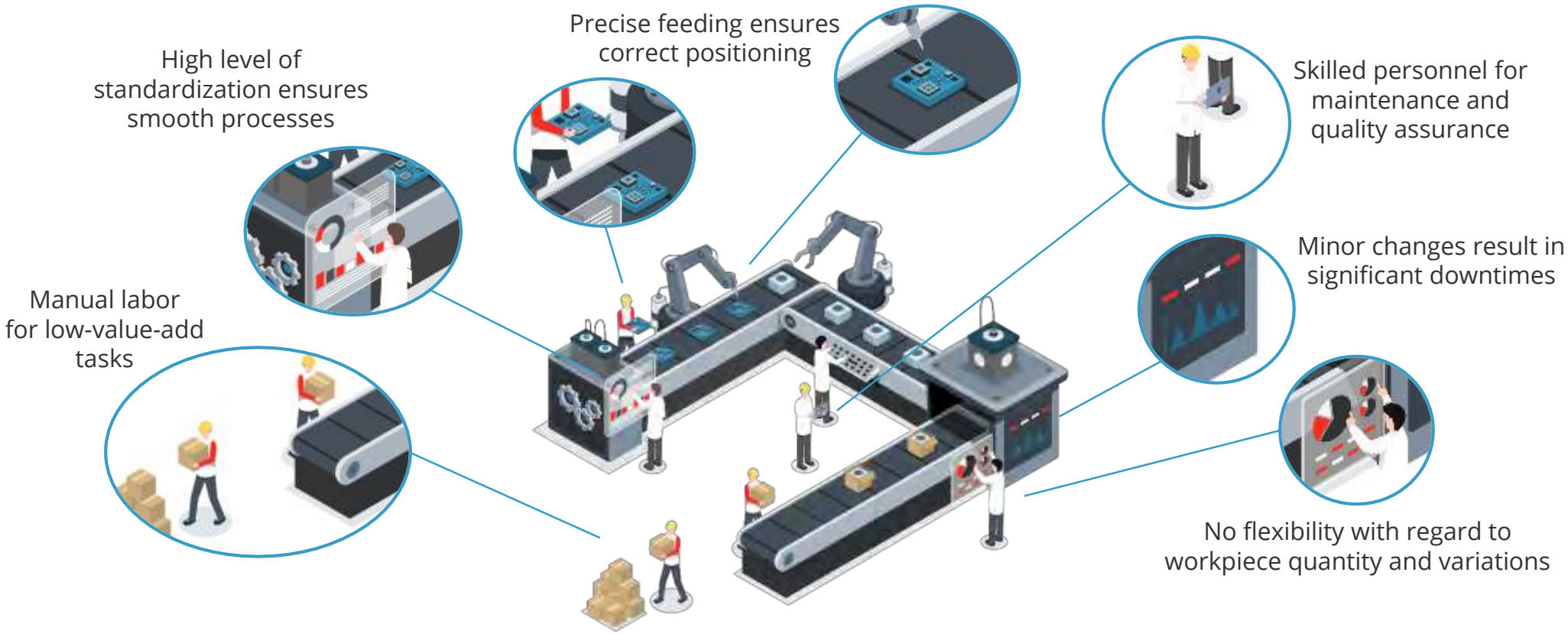


Good Data for Pick-and-Place in Agile Production

Dr. Michael Suppa

ROBOTS NOT SMART ENOUGH FOR NEXT-LEVEL INDUSTRY 4.0

- Potential offered by automating simpler use cases has been exhausted
- Next evolutionary step for Industry 4.0 is urgently needed
- Robots must be enabled to automate more complex tasks

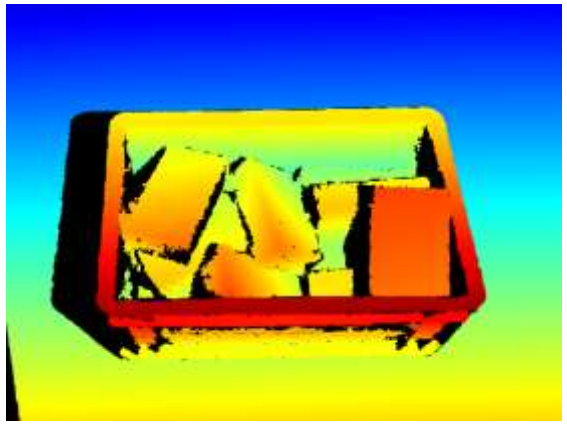


Why 3D Stereo?

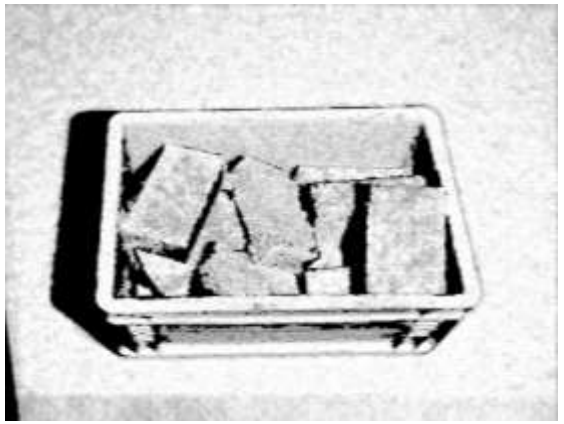
UNSTRUCTURED ENVIRONMENTS REQUIRE 3D DATA

- Stereo delivers RGB-D data directly synchronized in time and calibrated
- Increase in computing resources allows for onboard computation in real-time
- Depth is needed for accuracy and flexibility, images are the key data base for machine learning
- Combination of algorithms and machine learning in one system

Camera Image



Depth Image



Confidence Image

3D Reconstruction

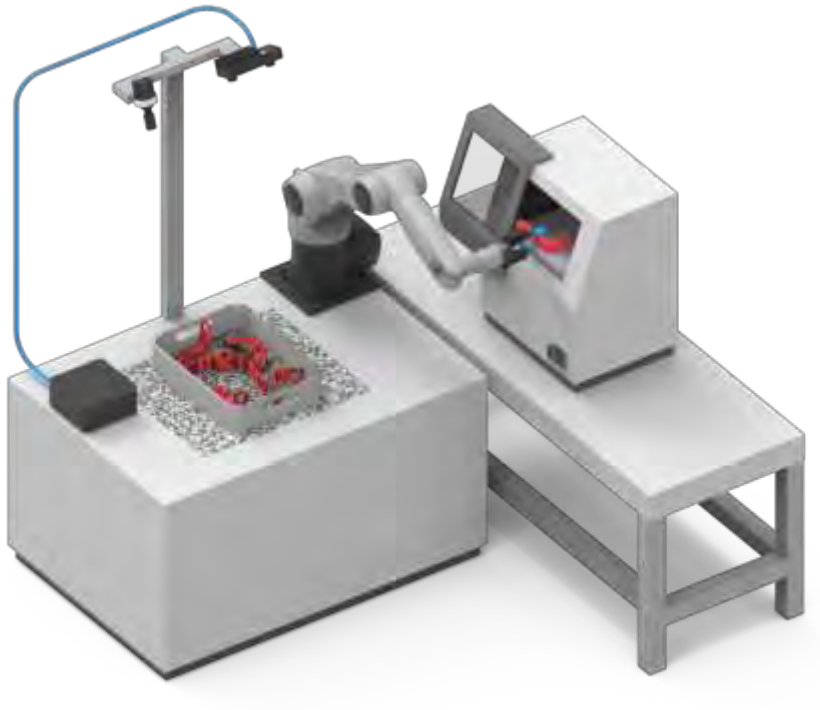
roboception

rc_reason CADMatch

ROBOTIC MACHINE TENDING

Detects position and orientation of objects using CAD models.

- Detection and localization of objects based on CAD data
- Delivers grasp point(s) for reliable pick-and-place
- Grasp teaching interface
- Applied AI-based part training process
- Works with static and robot-mounted sensors coupled with rc_randomdot pattern projector
- Runs offboard on rc_cube



roboception

rc_reason CADMatch

TWO-STAGE DETECTION USING CAD MODELS

Stage 1: Object detection and pose estimation using machine learning (CNNs). Automated training procedure on simulation images, no manual labeling required

Stage 2: Object pose refinement to reach target accuracy

roboception

rc_reason CADMatch

FROM 3D CAD MODEL

Input data to template generation pipeline:

- CAD model (with sub-millimeter accuracy)
- Picture of the part
- Application description, e.g. use-case (bin picking, structured picking) and expected working range

CAD model and use-case data

Generated CADMatch template file (.rccmt)

CADMatch Simulation Report

Template Optimization:

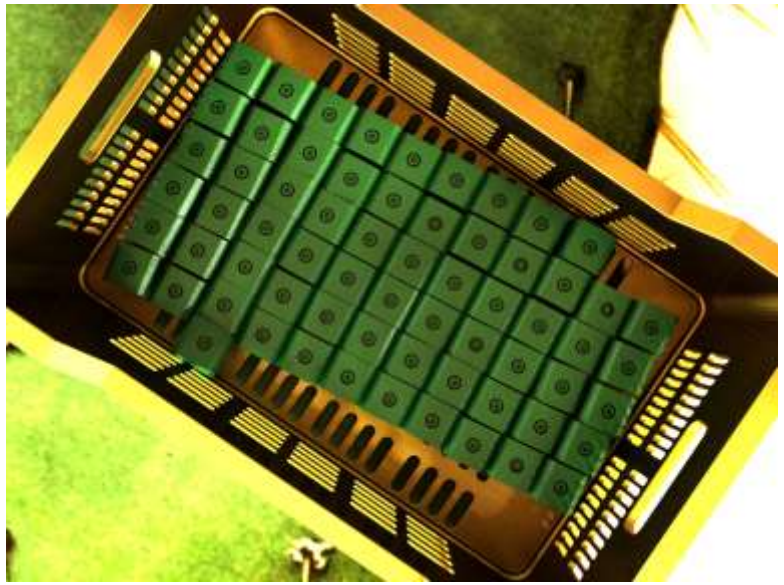
- Parameter optimization using recorded data
- Training data set (approx. 300 simulated images) enrichment with real data (1-5 images)

roboception

CADMatch Template Generation

SIMULATION ENVIRONMENT

- Training images generated in a photorealistic simulation environment
- Large material library for robustness against color response and lightning conditions
- Requires **no on-site** data recording
- Support for different use-cases and multi-material parts



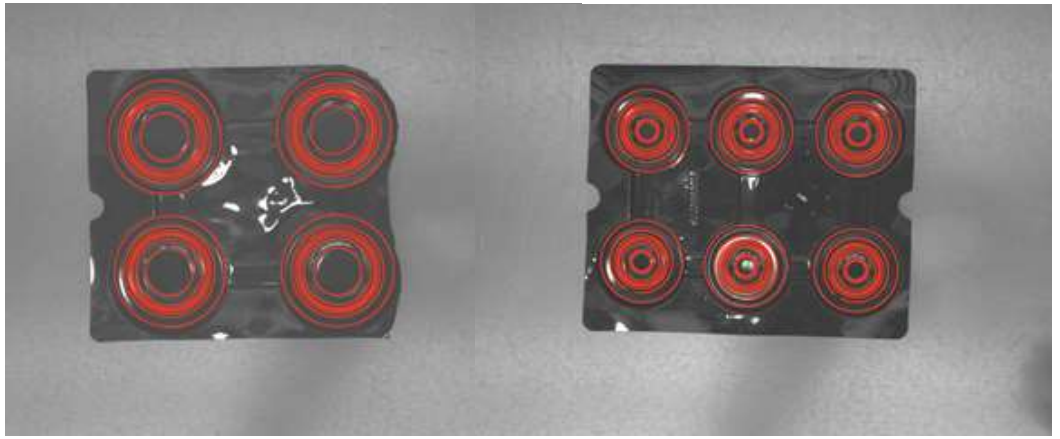
Template Generation Service

1. **Preparation phase:** Uploading of CAD models, preparation of the model, and validation with the user.
2. **Generation phase:** The generation workflow is executed automatically without user input.
3. **Feedback phase:** The user is informed on the success and receives a template for download. If the result needs to be discussed e.g. regarding detection accuracy, the user is contacted and the results will be discussed

Pilots in the ODIN Project

White Goods Pilot Use Case

- CADMatch is used for the detection of cook tops
- Challenge: Black cook tops are provided in a dark template
- Approach:
  - Generation of detection templates based on CAD data
  - Template optimisation by adding real data and/or changing detection parameters



Aeronautics Pilot Use Case

- CADMatch is used for the detection of fan cowl templates
- Challenge: Robot view points, dark background and high accuracy requirements
- Approach:
  - Generation of detection templates based on CAD data

Further information:D2.1 ODIN Core Enabling technologies for perception enabled reconfigurable resources – Initial prototype

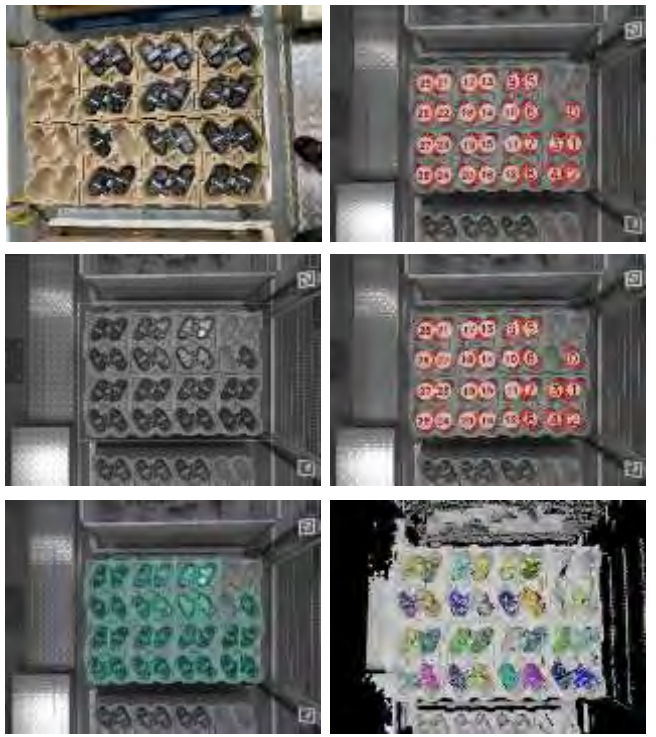
Flexible Production with Automated Kitting Processes

3D VISION INCREASES ROBUSTNESS AND REDUCES CYCLE TIME

> *The new cell is running robustly and adapts to changes [...] reduced the cycle time from 40 to 25 sec; a pick-and-place operation takes 7 instead of 12 seconds."*

Autonomous compilation of different parts, picked directly from the supplier's pallets, into kitting trays; cell size ~5x3 m²

- Two rc_viscores on rails above the cell detect even small parts with sub-mm precision based on CAD template
- rc_cube runs sensors, rc_reason CADMatch software and individual sorting strategies
- AprilTags and a tailored software module in the rc_cube's UserSpace (no additional computing resources)



Customer	Danfoss Drives A/S, Grasten (Denmark)
Product(s)	2x rc_viscore, rc_cube, individual software solution in UserSpace
Status	In operational use at Danfoss' Grasten facility, with roll-out to other sites foreseen
Online	https://roboception.com/en/use-case-automated-kitting-solution-with-robot-vision/

Flexible Production with Automated Kitting Processes

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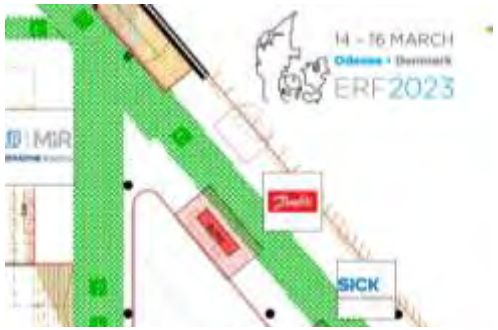

Visit Danfoss in the **exhibition area** to learn more about the use case

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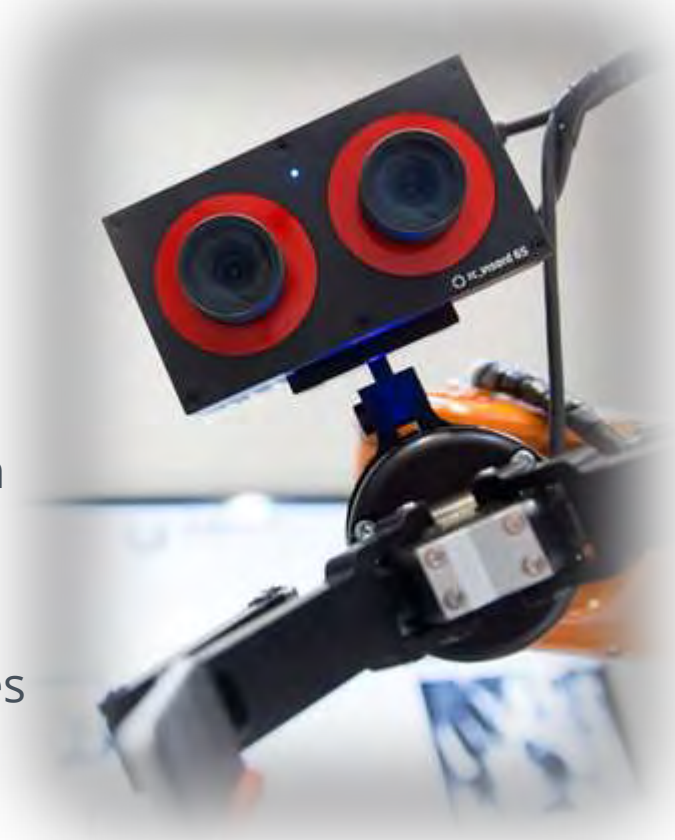
Good Data for Pick-and-Place in Agile Production

- 3D vision enables automation of complex cases also for small lot sizes
- Onsite downtimes and recording times can be reduced massively by using simulations/digital twins
- No vision expertise is needed to implement vision in production
- Automation in flexible production becomes possible and feasible in SMEs and large companies



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We are looking forward doing business with you!

Dr. Michael Suppa
CEO & Co-Founder

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Round Table Discussion

14 – 16 MARCH
Odense • Denmark
ERF2023

EUROPEAN
ROBOTICS
FORUM

eu ROBOTICS

10th anniversary
FOUNDED SEPTEMBER 2012

From Good Data to Ease of Use

#1
GOOD DATA INSTEAD OF BIG DATA REDUCES ONSITE TRAINING TIME

- Simulation helps create realistic training data using model-knowledge
- Ground truth can be used in the training
- Enrichment with real data images instead of complete data recording process
- Results in accuracy in mm and not detection rates in percent

#2
SCALABLE ML SOFTWARE PLATFORM FOR PLUG-AND-PRODUCE

- Share ressource by deployment concept
- Allow integrators and end customers to add modules on the same plattform
- Smart Sensors allow for distribution of computing ressources

#3
USING ML TO ENSURE EASE-OF-USE FOR NON-VISION EXPERTS

- ML reduces the parameter space for the customer
- Web Interfaces with wizards allow for non-expert use

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EUROPEAN ROBOTICS FORUM

Key Questions

- Synthetic training data generation requires model data for simulation. Do you have this data available and how exact is it?
- For unknown objects, real data is required in addition to synthetic data. Which ratio of real data to synthetic data is feasible in your use case?
- Which level of expertise regarding 3D vision and machine learning is available in your area? (none, beginner, moderate, expert)

slido

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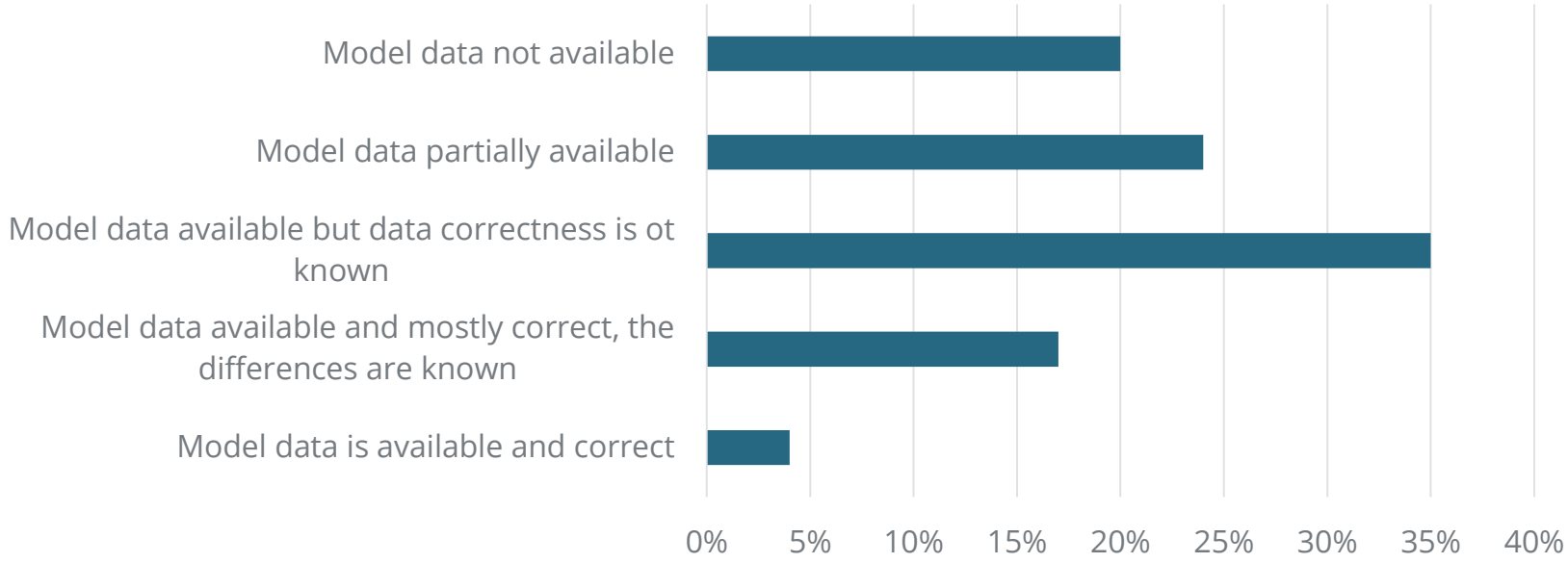

slido

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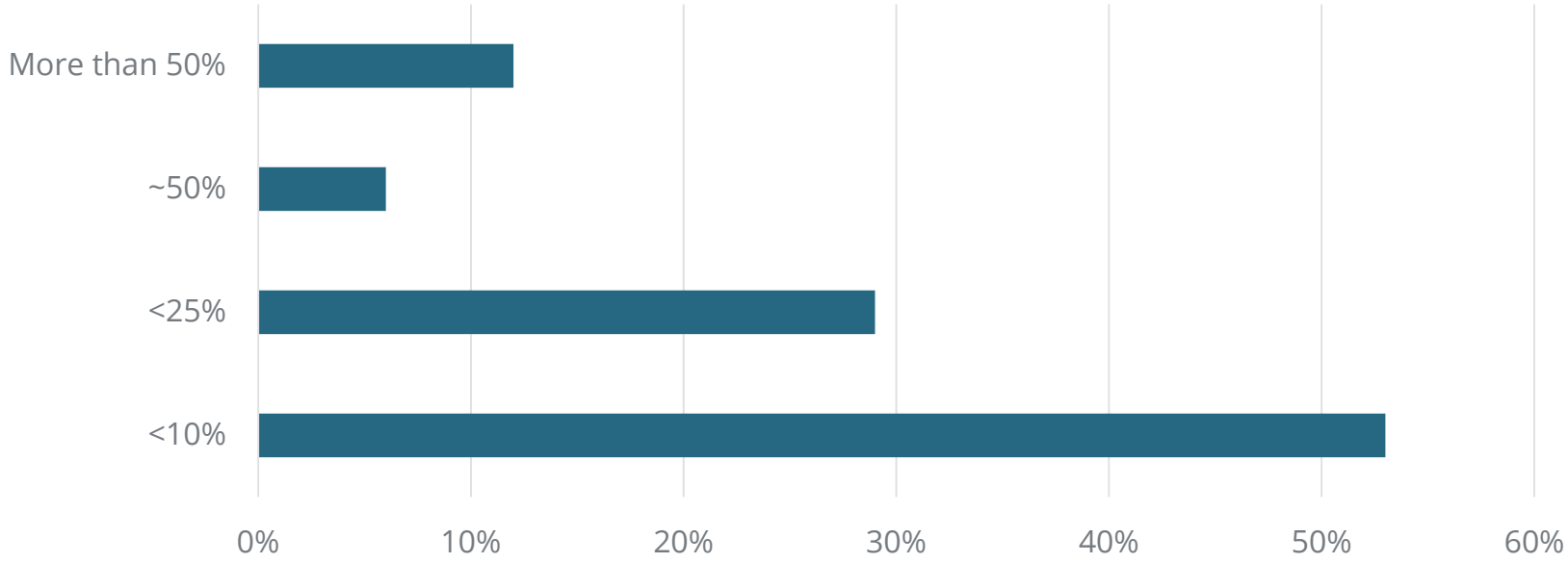
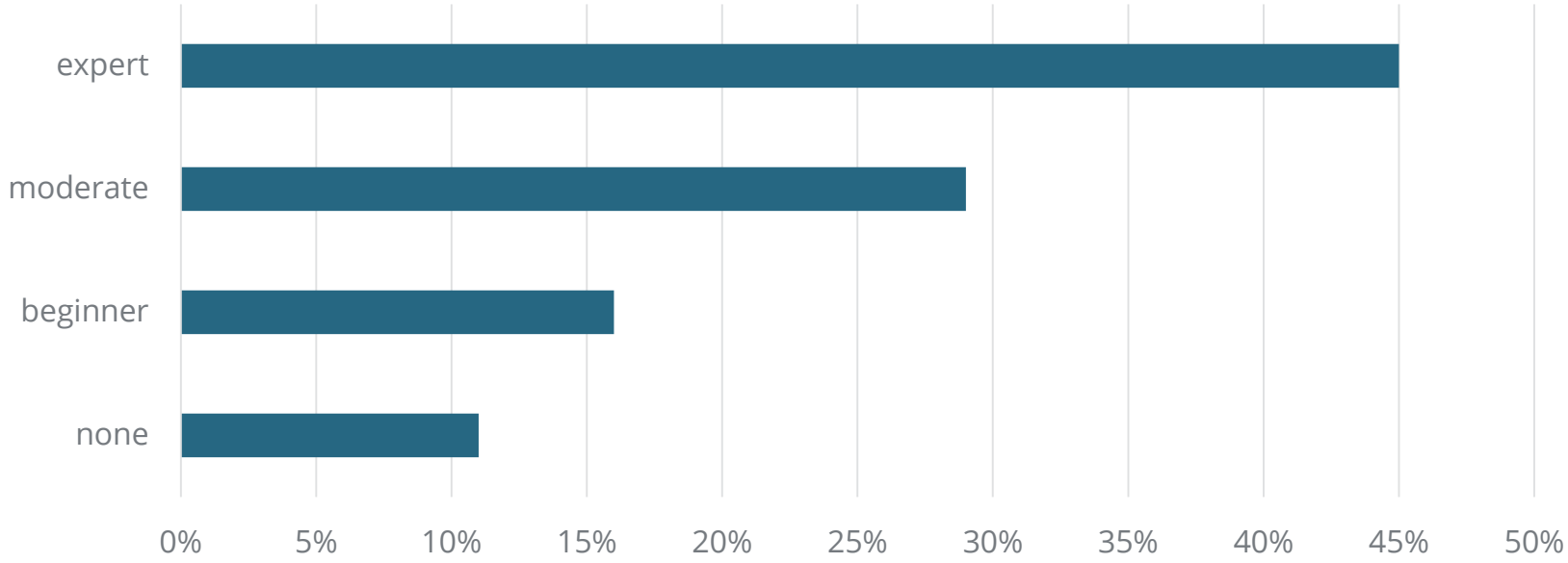


slido

Which level of expertise regarding 3D vision and machine learning is available in your area?



Panel Discussion

Prof. Markus Vincze
TU Vienna, Austria

Dr. Radhika Gudipati
Ocado Technologies, UK

Dr. Patrick Courtney
Tec-connection, UK

Dr. Michael Suppa
Roboception GmbH, Germany

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EUROPEAN ROBOTICS FORUM

Topic Group Perception

Slides will be published on the website:
https://roboception.com/en/innovation-en/erf2023/

Interest in participating in TG Perception:
michael.suppa@roboception.de

and/or registration at
https://sparc-robotics-portal.eu/