Machine Learning in Robotics at CERN

ELLIS-CERN Workshop

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BE-CEM-MRO
CERN

Outline

- Our Robots and Software Framework
- Our Operator Interfaces
- Our Approach
- Next Steps

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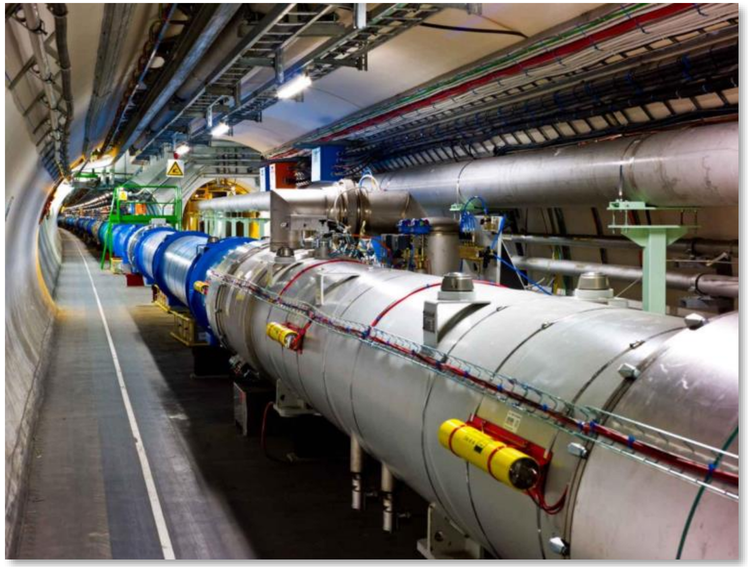
Our Needs

- **Inspection, operation and maintenance of radioactive particle accelerators devices towards maintainability and availability increase**
  - ✓ **Experimental areas and objects not built to be remote handled/inspected**
    - ✓ Any intervention may lead to "**surprises**"
    - ✓ Risk of **contamination**



The LHC tunnel

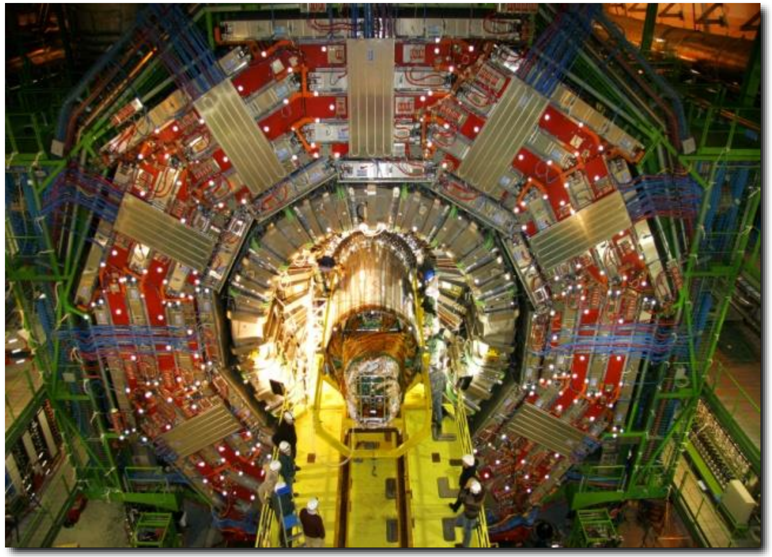
North Area experimental zone

Radioactive sample handled by a robot

The Challenges

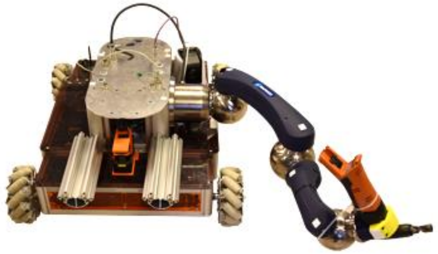
- Maintenance, intervention and inspection in harsh and semi-structured environments
- Radiation, magnetic disturbances, delicate equipment not designed for robots, big distances, communication, time for the intervention, highly skilled technicians required (non robotic operators), etc.

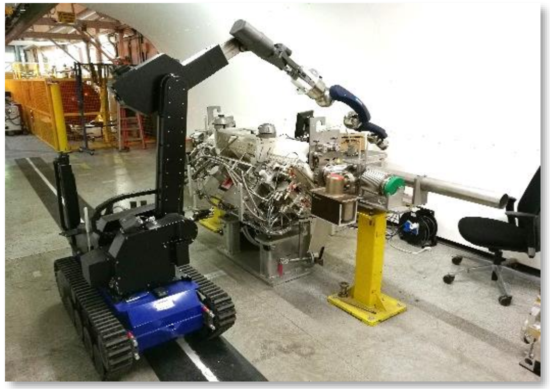


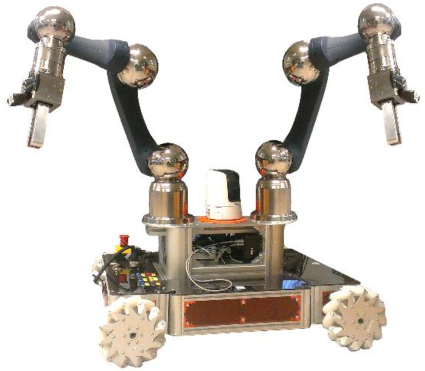
Robots at CERN

Train Inspection Monorail (CERN made)





EXTRM robot (CERN made)

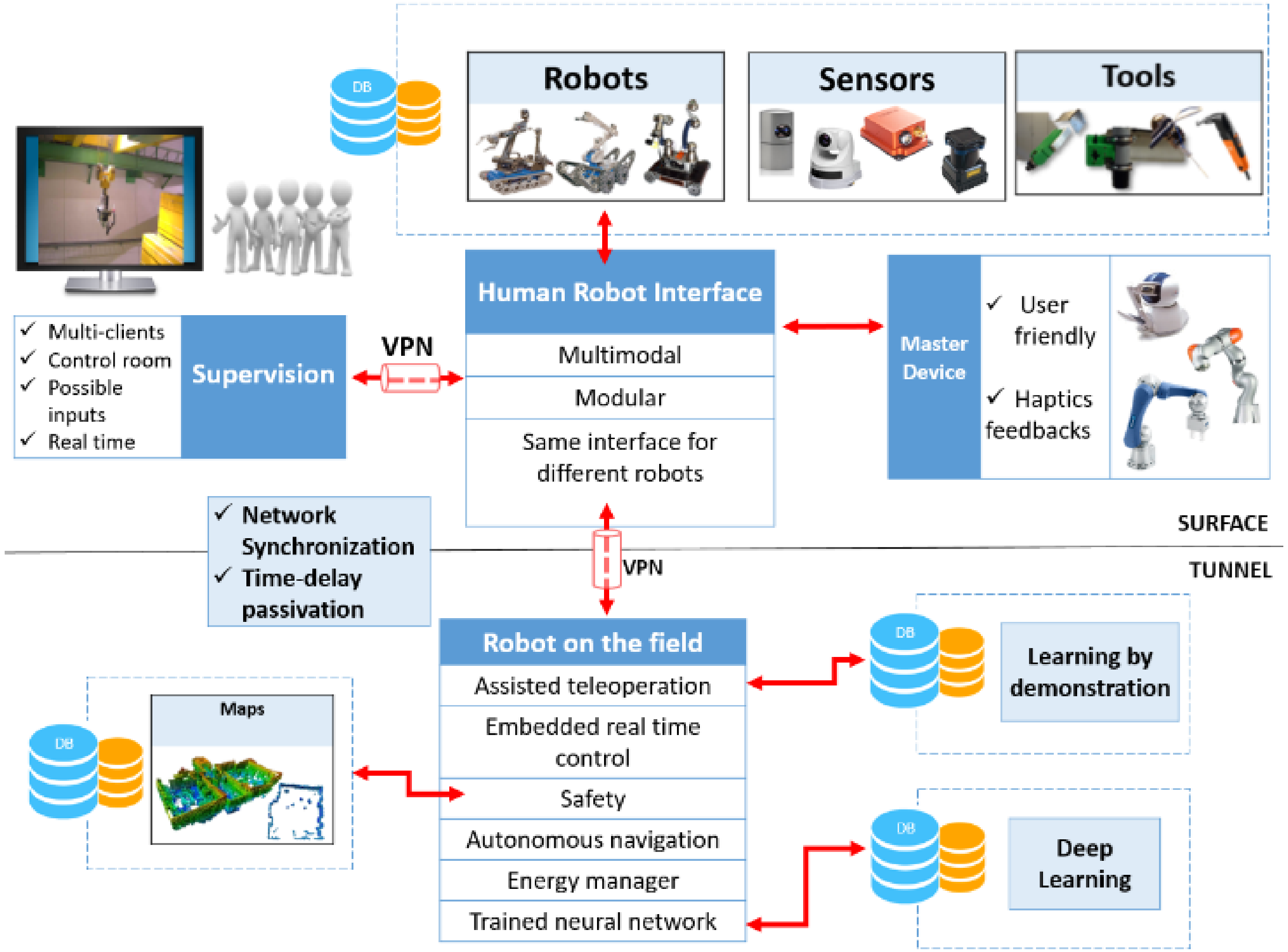


CERNBot in different configurations (CERN made)

[Mario Di Castro, Alessandro Masi, Luca Rosario Buonocore, Manuel Ferre, Roberto Losito, Simone Gilardoni, and Giacomo Lunghi. Jacow: A dual arms robotic platform control for navigation, inspection and telemanipulation. 2018.]

[Di Castro, Mario, et al. "i-TIM: A Robotic System for Safety, Measurements, Inspection and Maintenance in Harsh Environments." 2018 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR). IEEE, 2018..]

Control Framework

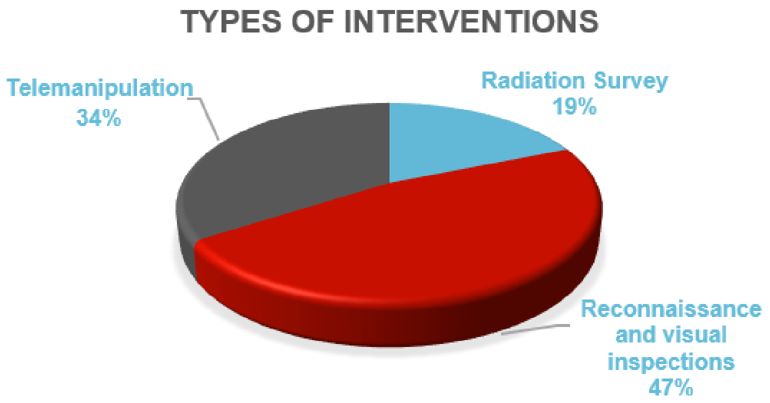


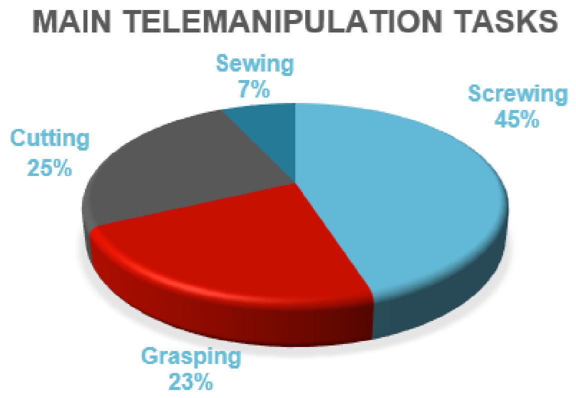
CERNTAURO Architecture

- [Giacomo Lunghi, Raul Marin Prades, and Mario Di Castro. "An Advanced, Adaptive and Multimodal Graphical User Interface for Human-robot Teleoperation in Radioactive Scenarios." ICINCO (2). 2016]
- [Giacomo Lunghi, Raul Marin Prades, Mario Di Castro, Manuel Ferre, and Alessandro Masi. "An RGB-D based Augmented Reality 3D Reconstruction System for Robotic Environmental Inspection of Radioactive Areas." In ICINCO (2), pp. 233-238. 2017.]
- [Giacomo Lunghi, et al. "Multimodal Human-Robot Interface for Supervision and Programming of Cooperative Behaviours of Robotics Agents in Hazardous Environments: Validation in Radioactive and Underwater Scenarios for Objects Transport." (2018)]
- [Mario Di Castro, Manuel Ferre, and Alessandro Masi. "CERNTAURO: A Modular Architecture for Robotic Inspection and Telemanipulation in Harsh and Semi-Structured Environments." IEEE Access 6 (2018): 37506-37522]

Operations

Nr. of Interventions in the last 48 months	Nr. of tasks performed in the last 48 months	Robot operation time in harsh environment [h]
140	250	~ 300



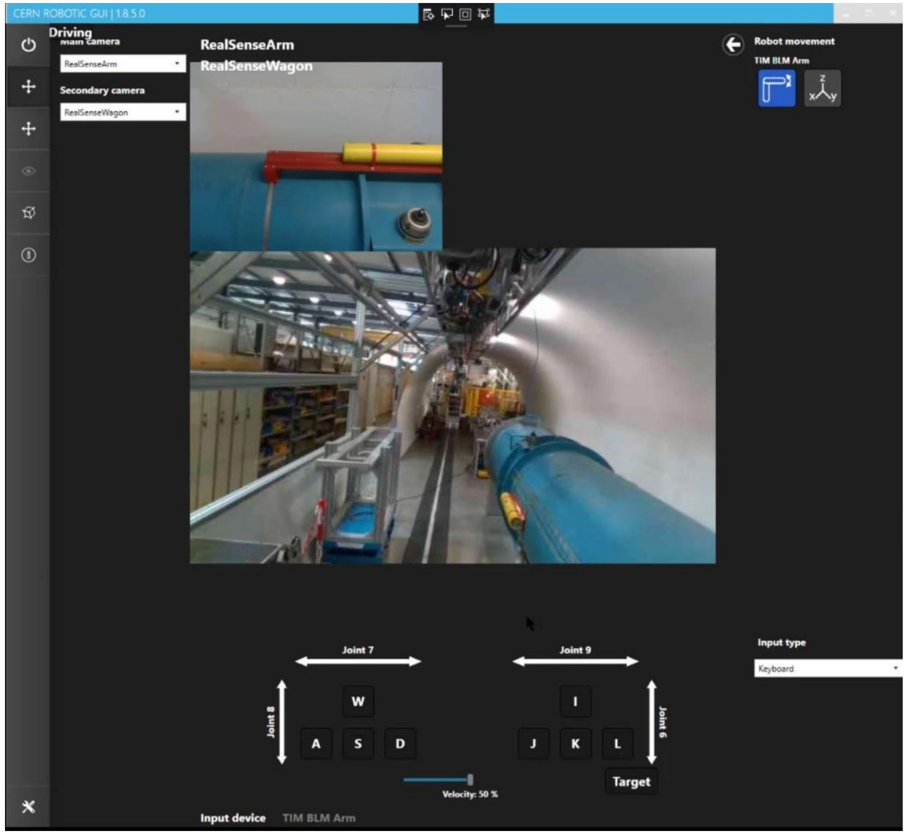


Continuing developing best practice for equipment design and robotic intervention procedures including recovery scenarios

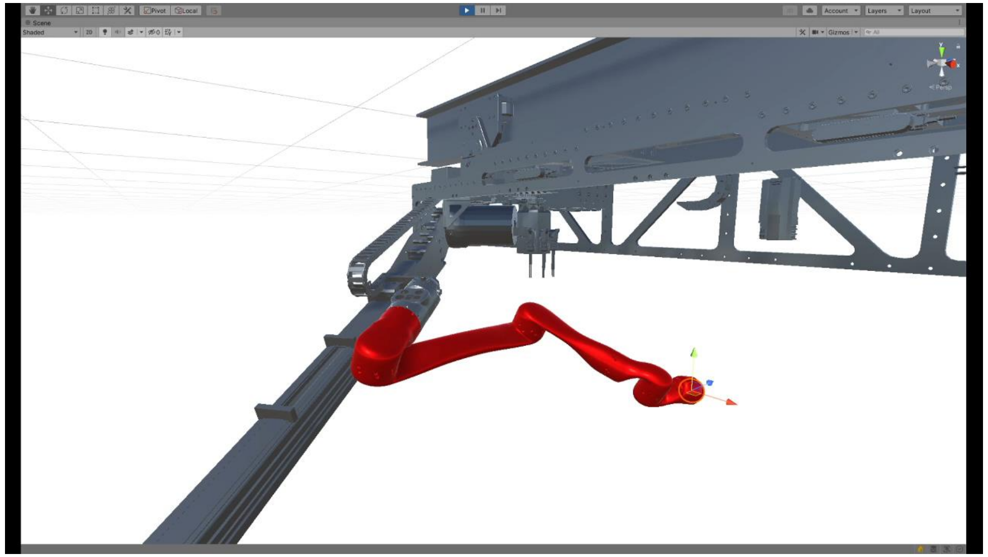
Outline

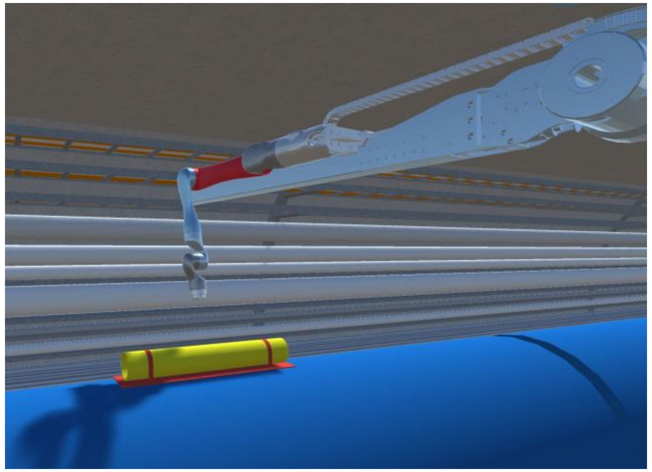
- Our Robots and Software Framework
- **Our Operator Interfaces**
- Our Approach
- Next Steps

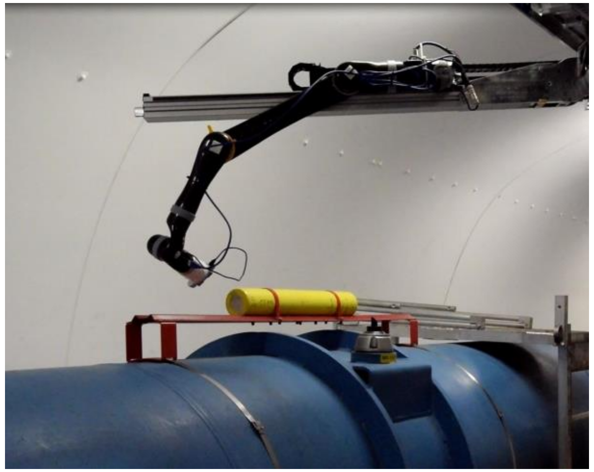
2D GUI Interface

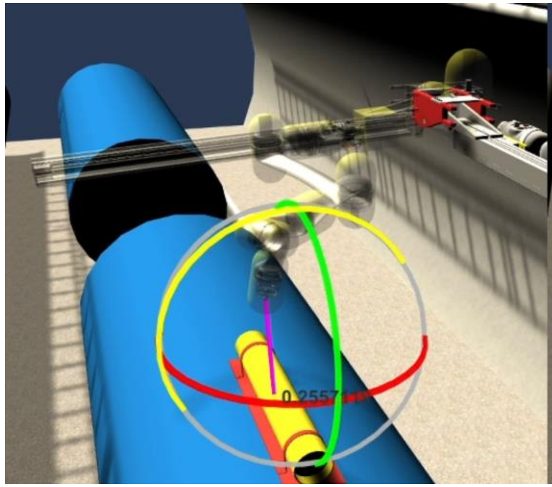


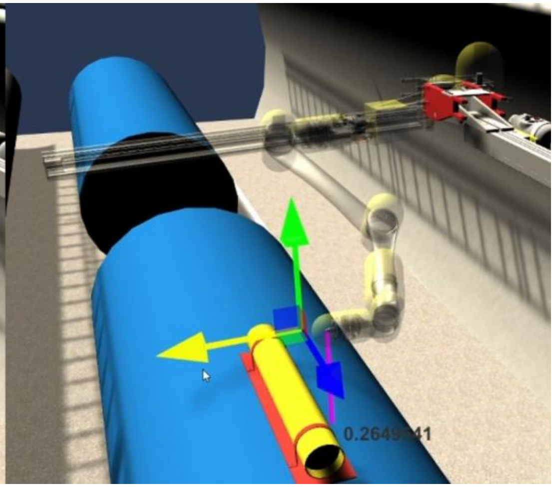
3D GUI Interface Research

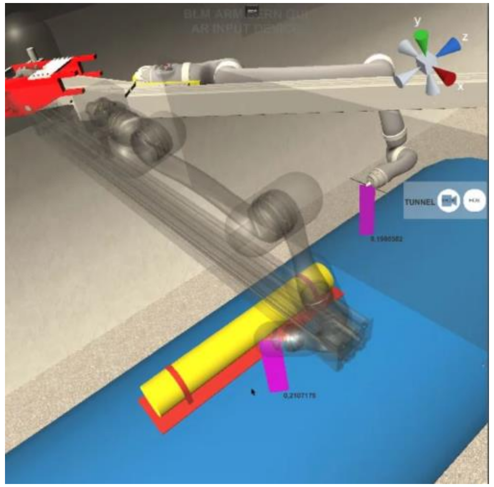












BLM Measurements – Unity Interface
Credit: *Krzysztof* Szczurek,
PhD CERN

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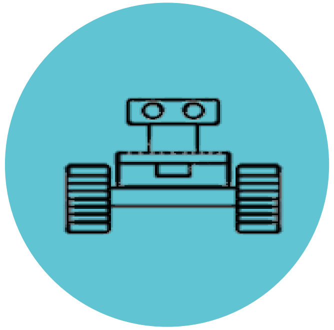
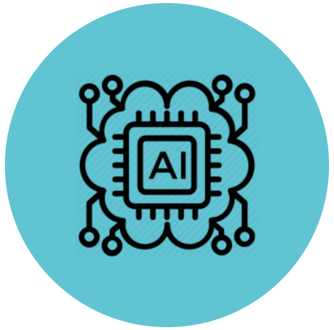
Our Approach



ROBOTICS

COMPUTER VISION



MACHINE LEARNING

Machine Learning in Robotics

- Great advances in robot vision thanks to supervised deep learning techniques
  - Accuracy in object tracking (Fast-RCNN, Mask-RCNN)
  - Object grasping points calculation
- Control of closed chains kinematic robots
  - Still an open issue, Long short-term memory (LSTM) networks for system dynamic learning
- Advances in situation awareness for autonomous behaviors
  - Possibility of learning to predict external changes in the environment
- Human-Robot collaboration
  - Advances in speech recognition, gesture recognition, human action prediction

Grasping points for everyday objects [2]


Saliency detection (center of attention) in self-driving cars for situational awareness [3]

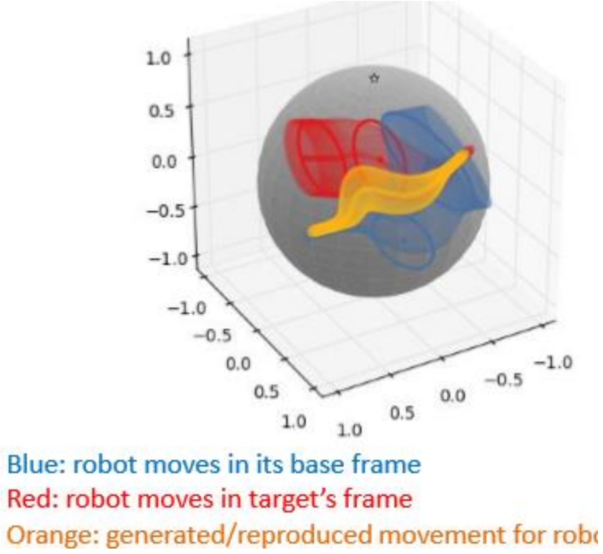

Human Robot collaboration for mechanical assembly

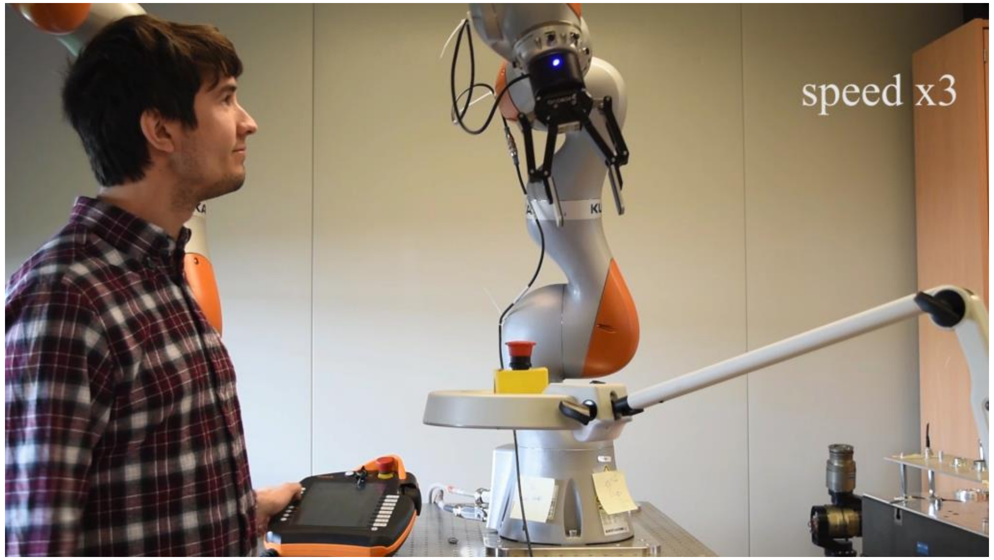
Object Detection & Recognition for Teleoperation

- Machine learning (Faster-RCNN) is used to assist online grasping tasks in teleoperation Visual servo control endorsed with AI
  Di Castro, Mario, Manuel Ferre, and Alessandro Masi. "CERNTAURO: A Modular Architecture for Robotic Inspection and Telemanipulation in Harsh and Semi-Structured Environments." IEEE Access 6 (2018): 37506-37522.
- Object detection embedded in CERN Human-Robot Interface to process live images endorsed with super resolution techniques
  Lunghi, Giacomo, Raul Marin Prades, and Mario Di Castro. "An Advanced, Adaptive and Multimodal Graphical User Interface for Human-robot Teleoperation in Radioactive Scenarios." ICINCO (2). 2016.

Learning by Demonstration

- **Machine imitation learning**
  - ✓ Generate movement trajectories using Gaussian Mixture Model (GMM) on a Riemannian manifold from several human demos and Dynamic Movement Primitives (DMP)
- **Learning Benefits**
  - ✓ Robots adapted to the tasks and the environment
  - ✓ Fully autonomous task implementation possible
  - ✓ Assistive robotic technology supporting remote operators

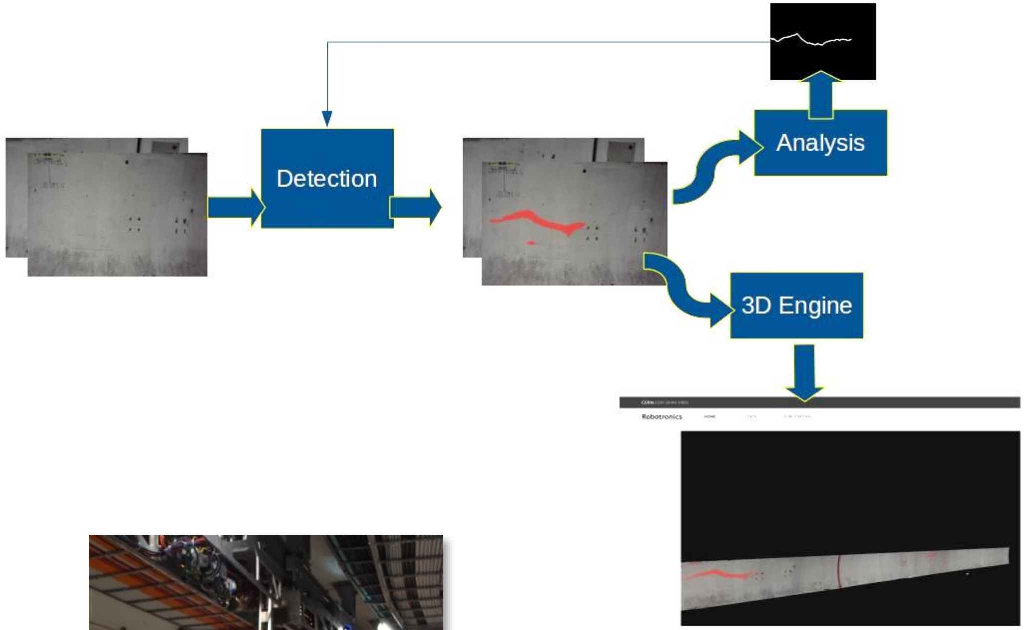




Online Tunnel Structure Monitoring

Requested by SMB

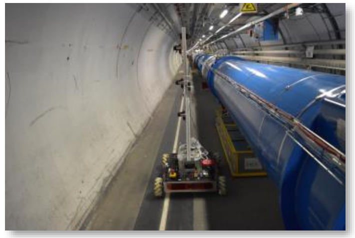
- Detects defects (cracks, water leaks, changes [13-14]) using a Mask-RCNN network.
- High-definition picture collection using TIM and CERNBot
- 3D reconstruction of wall using Structure from Motion techniques to compare time evolution of defects (available on web browser or virtual reality headset)
- **HL-LHC condition survey of existing infrastructure carried out with TIM to monitor impact of new civil works**



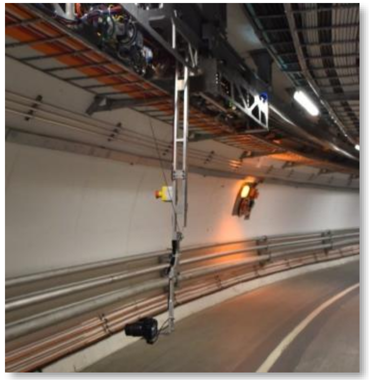
Example of water leak found by TIM2 during TS3 2018

Example of crack found using vision based machine learning techniques

HD camera system for tunnel dome view



System integrated also on other robots

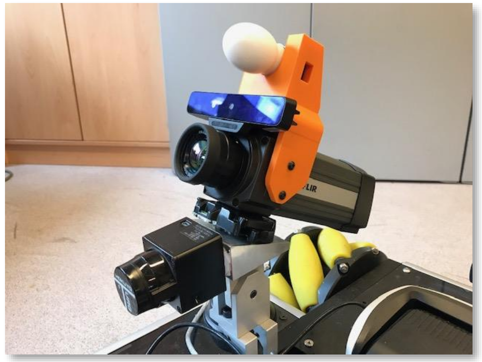


HD cameras mounted on TIM

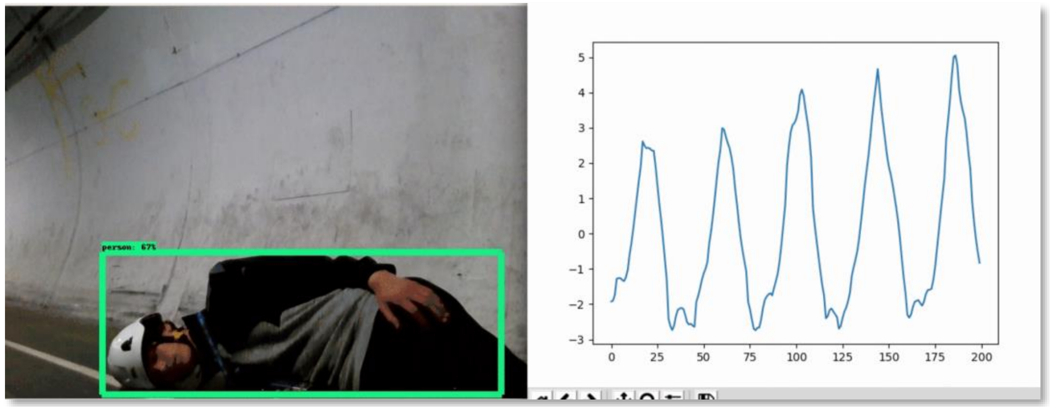
People Recognition and Vital Monitoring

Requested by HSE

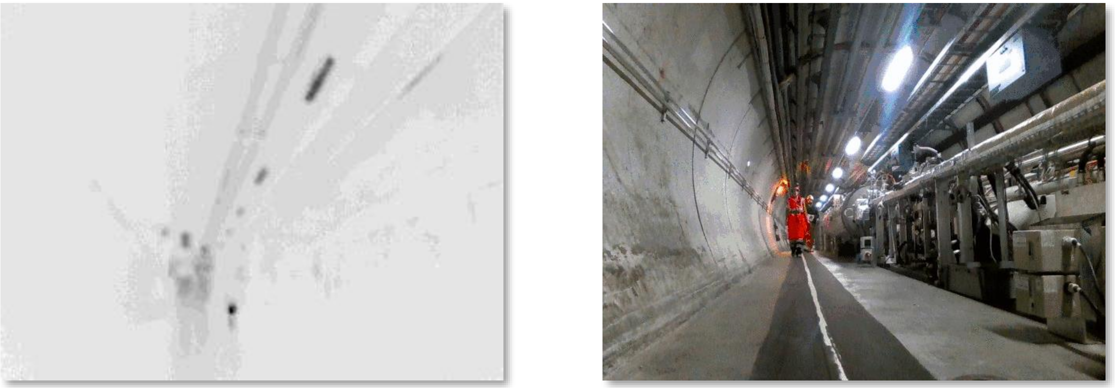
- Machine learning techniques enhance people detection and vital signals monitoring at distance
- People search and rescue is of primary interest in disaster scenarios
- People monitoring during rehabilitation



Vision system (2D Laser, radar, thermal and 2D-3D camera)



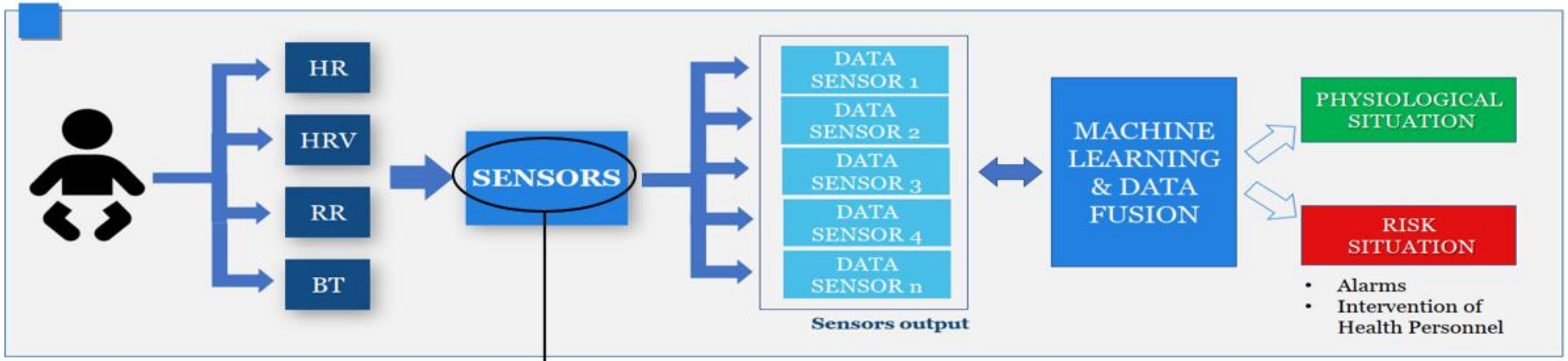
Online respiration monitoring



Online people recognition and tracking

People Recognition and Vital Monitoring

- MARCHESE: Machine leArning based human ReCognition and HEalth monitoring SystEm

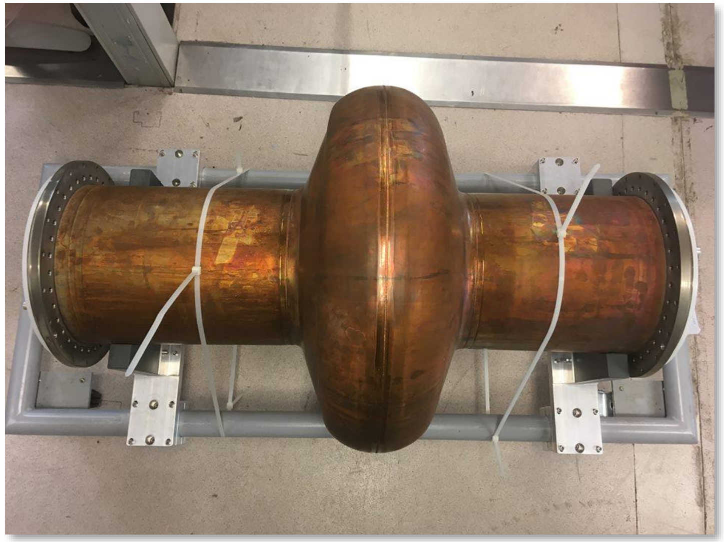


- Monitoring of physiological signals in **contactless way** using different sources of information.
- **Machine learning** using to match together different kind of signals coming from different sensor and obtain a reliable estimation of **patient's health state**.
- Focus on **neonate** born preterm.

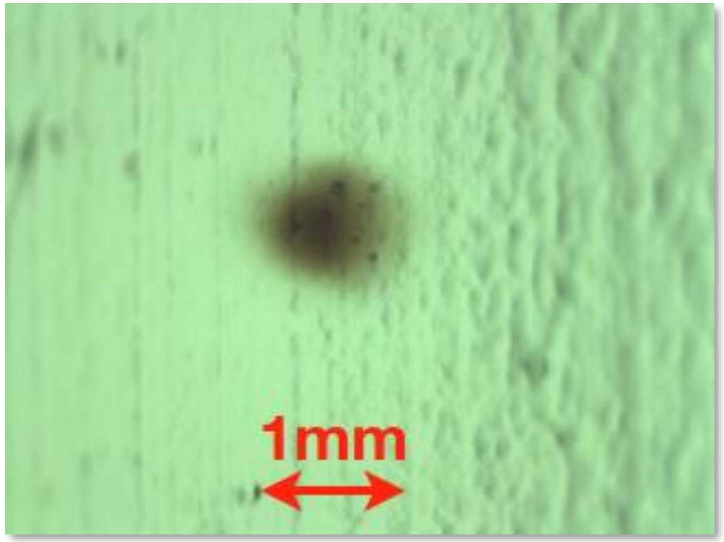
Visual based RF Cavities Quality Control

Requested by BE-RF

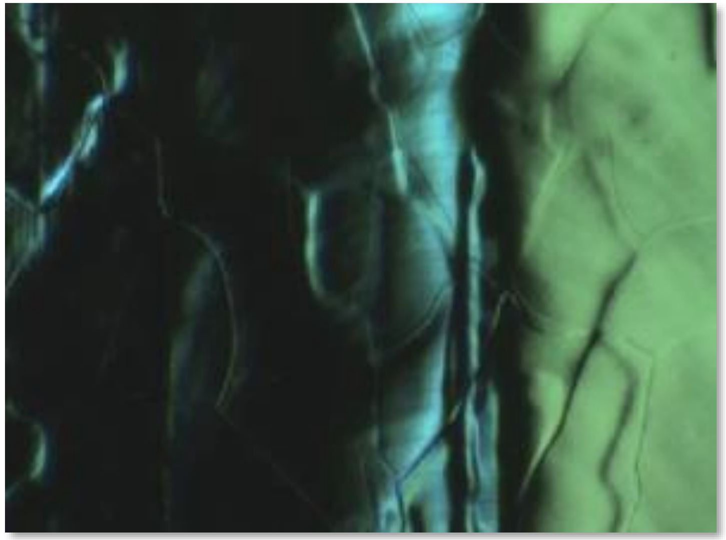
- Same technique used for defect detection is applied to surface quality control of the HL-LHC RF cavities



HL-LHC RF cavity



Anomaly (burn)



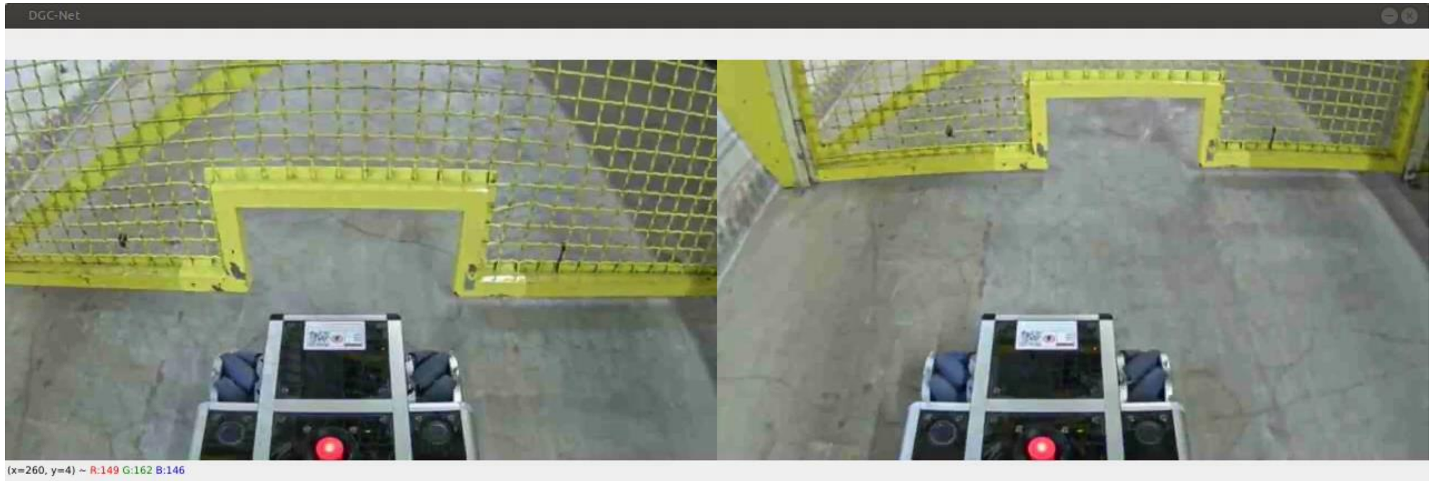
Welding cracks

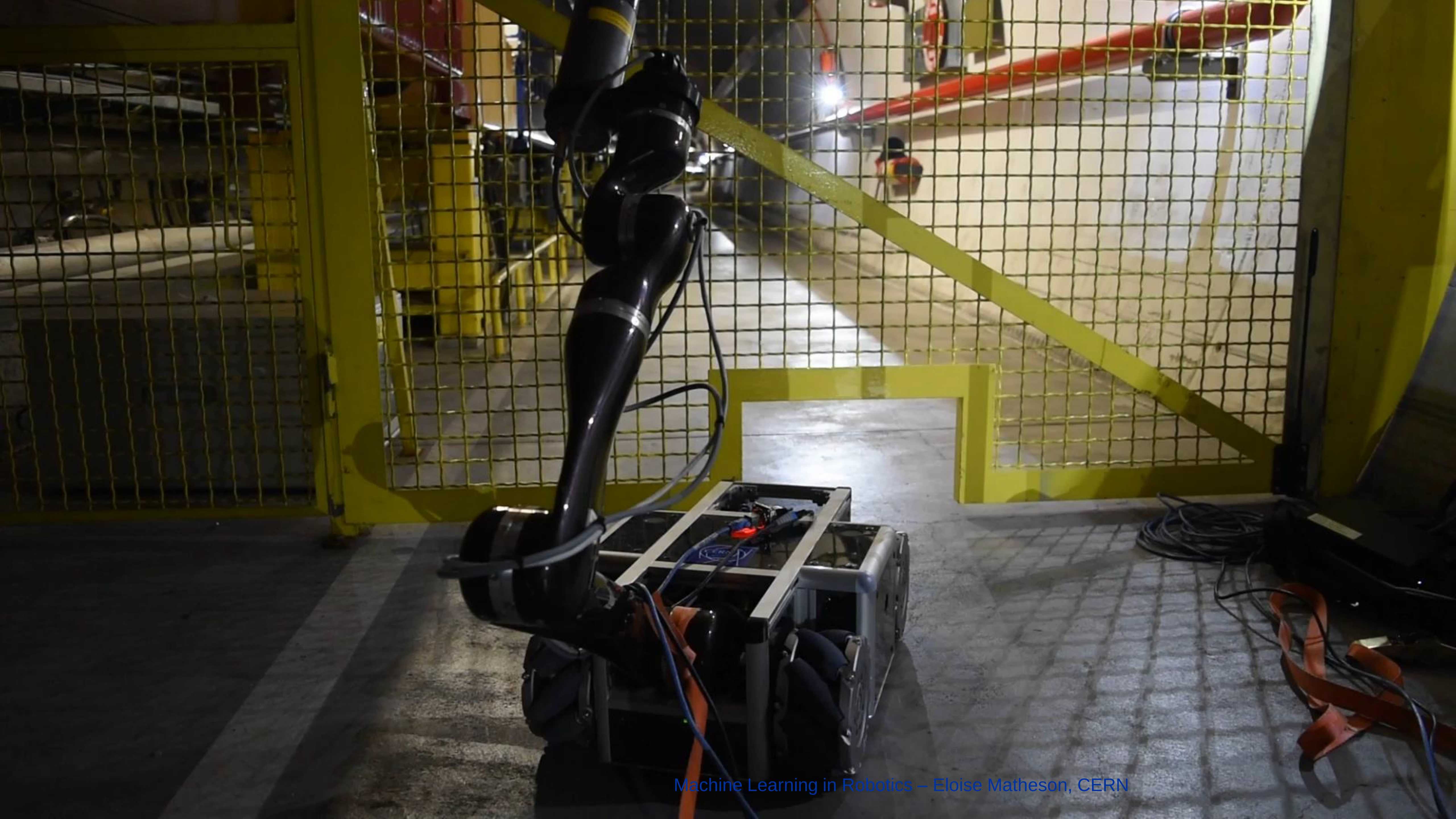
Courtesy of A. Macpherson

Autonomous Navigation

- ➢ Autonomous sector door detection, recognition and passage – heavily relies on vision

- ➢ Research into optical flow and deep learning to detect and perform pose estimation of the door – CNN-based dense pixel correspondence estimation
- ➢ Target Image + Source Image -> Aligned source image





+ others

Project effort over the last 5 years

- Work performed by several STAG, bachelor, master and PhD students

Università degli Studi di Napoli Federico II

Create

EPFL École Polytechnique Fédérale de Lausanne

ETH zürich

Università degli Studi di Genova

iit Istituto Italiano di Tecnologia

University of Zurich UZH

JKU Institut für Telekooperation

UCBM Università Campus Bio-Medico di Roma

Loughborough University

SDU

UJI Universitat Jaume I

L-Università ta' Malta

TUM

I.U.T Montpellier-Sete

Universidad de Oviedo
Universidá d'Uviéu
University of Oviedo

Tampere University of Technology

University of the Aegean

Università di Siena 1240

Universidad Politécnica de Madrid

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- Our Robots and Software Framework
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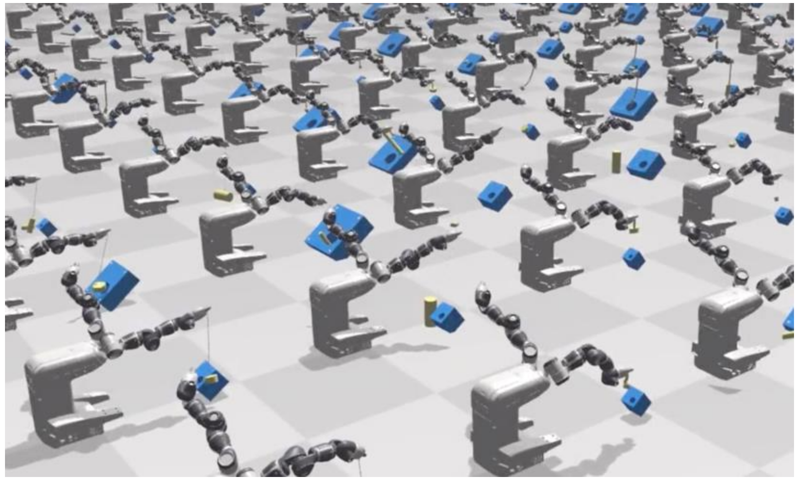
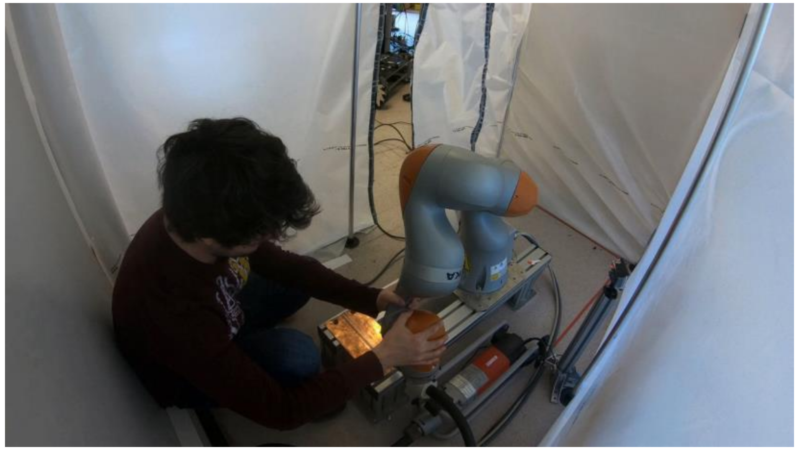
- **Next Steps**

Research

- Design of tools and equipment interfaces
  - ✓ Integration of standard gripper and tools with the equipment interface, simulation of how easy it could be to grasp and manipulate via machine learning algorithms -> **Optimized equipment interface design**
  - ✓ Integration of standard gripper and piece, simulation of which tool is the best to manipulate the piece -> **Optimized tool design**
  - ✓ **Risk analysis** to understand the chance of dropping or losing control
  - ✓ Auto-learn **recovery procedures**
- Design of interventions and/or robotic trajectories
  - ✓ Integration of action planning and event handling in simulation (**Learning in Simulation**)
  - ✓ Integration of operator actions before the intervention (**Learning by Demonstration**)
  - ✓ Leads to **shared control** between an operator and a robotic system, or **fully autonomous operations**





Easy Integration and Useability

- New approach to simplify the use of machine learning tools and algorithms
- Wrapper of widely used libraries allowing easier expandability
  - Lower learning curve
  - Less repeated code
  - Better overall understanding

Image > Tensor

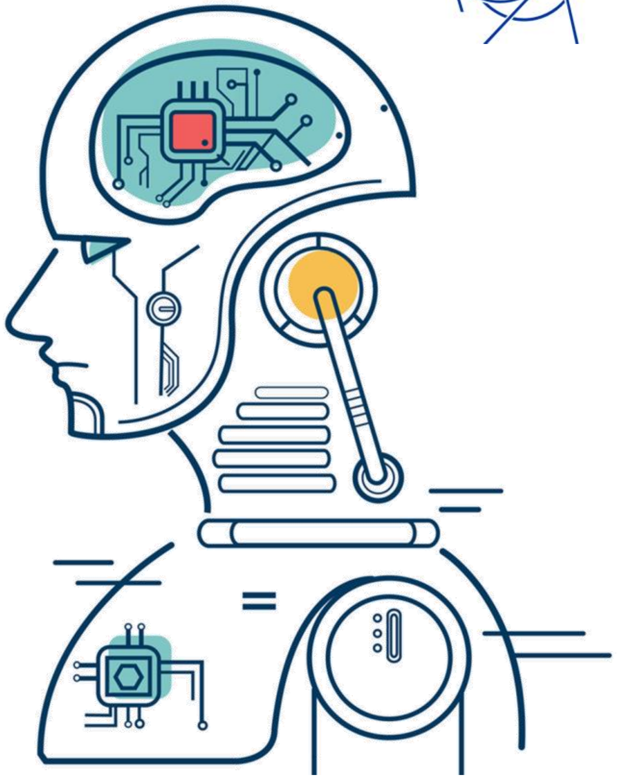
Inference

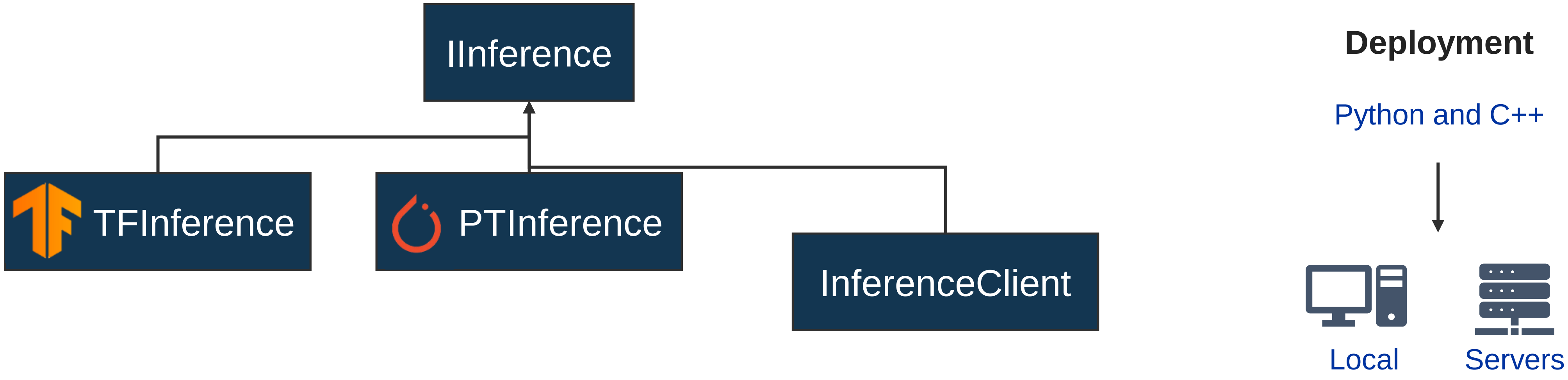
PyTorch

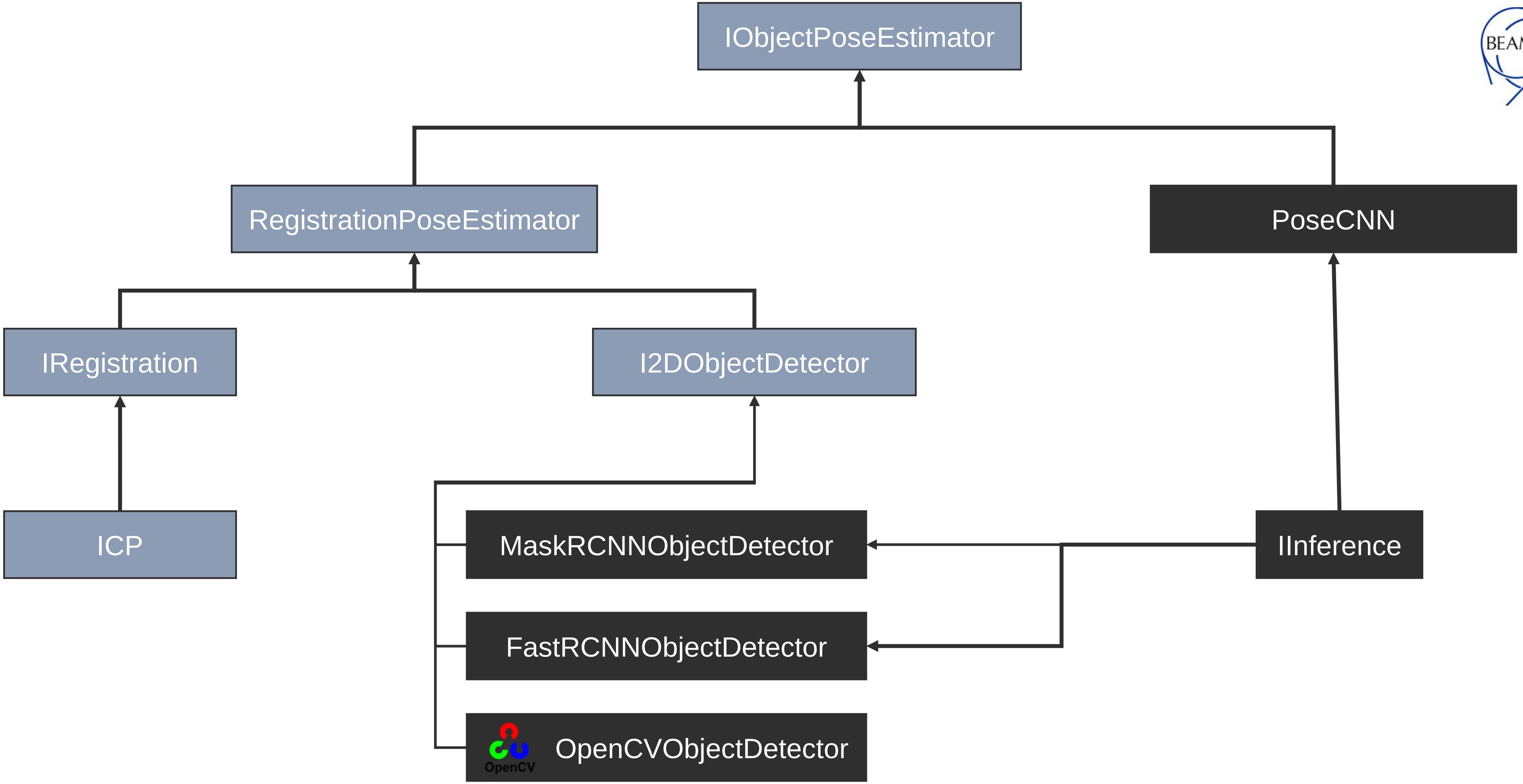
TensorFlow

TensorRT

Tensor > Bounding Box



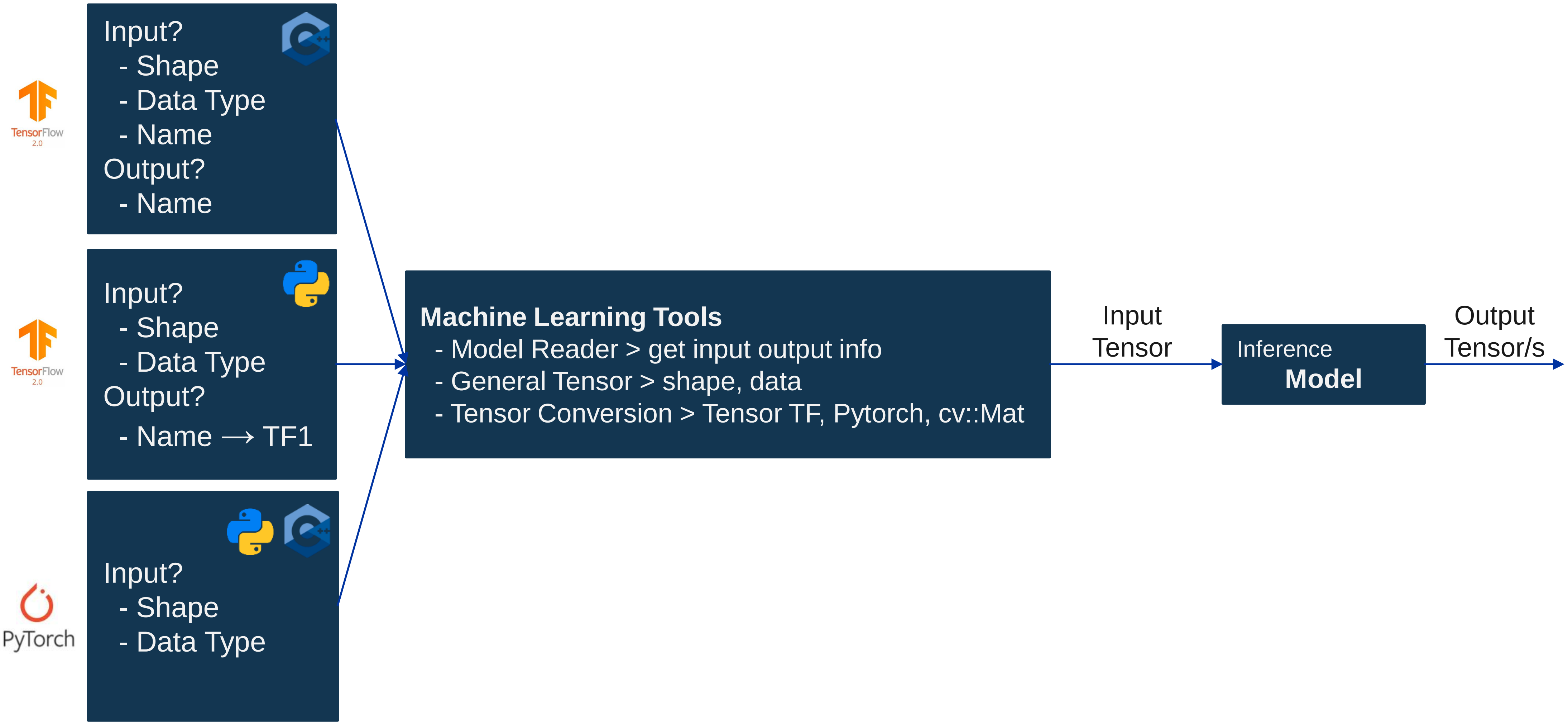

IInference
TFInference
PTInference
InferenceClient
Deployment
Python and C++
Local
Servers


IObjectPoseEstimator
RegistrationPoseEstimator
PoseCNN
IRegistration
I2DObjectDetector
ICP
MaskRCNNObjectDetector
FastRCNNObjectDetector
OpenCVObjectDetector
IInference

beams.cern

Internal Structure

Inference Structure



Machine Learning Tools

MODEL READER

TensorFlow

- TF1 → In C++
- TF2 → In Python

PyTorch

- PyTorch → No tool

Model Path → JSON Input and Output Information


```
{
    "Info": {
        "model_path": "/home/robotronics/Projects/blm_Mask_RCNN/blm
        "Library": "Tensorflow",
        "version": "2.x"
    },
    "Inputs": {
        "Input 0": {
            "name": "serving_default_input_tensor:0",
            "shape": [
                1,
                -1,
                -1,
                3
            ],
            "type": "DT_UINT8",
            "name key": "input_tensor"
        }
    },
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        "Output 0": {
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            "shape": [
                -1,
                4
            ],
            "type": "DT_FLOAT",
            "name key": "anchors"
        },
```

Machine Learning Tools

Tensor Class

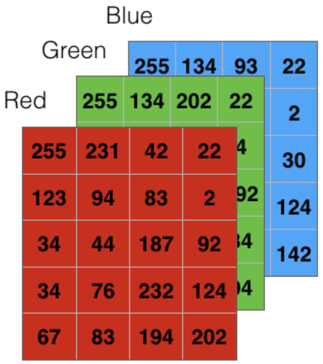
- Shape
- Data (1D Vector)

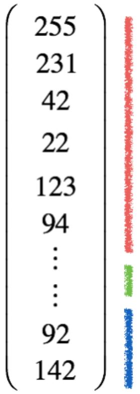
General Tensor

Shape
- (1200,675,3)

Data

TENSOR CONVERSION
- Mat2Tensor





TensorFlow 2.0
- TFTensor2Tensor
- Tensor2TFTensor

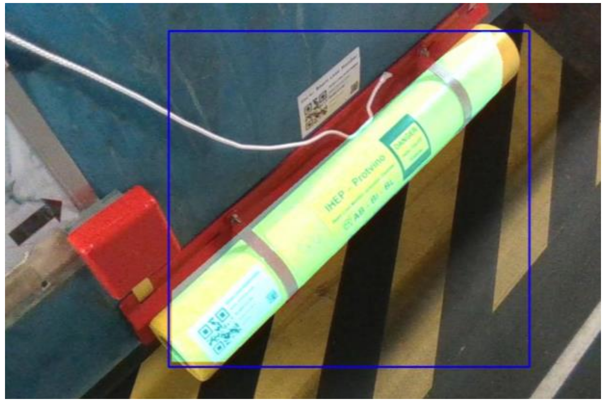
PyTorch
- PyTTensor2Tensor
- Tensor2PyTTensor

Inference

TENSOR CONVERSION

INPUT2TENSOR

IInference
- **TF1Inference**
- **TF2Inference**
- **PyTInference**



TFInference

TensorConversion
- Tensor2TFTensor

ModelReader
- Conversion correct shape
- Conversion data type
- Get name input (c++)
- get name output (TF1 c++ python)

Model Mask RCNN BLM detector

TensorConversion
- TFtensor2Tensor

Inference

TENSOR CONVERSION

INPUT2TENSOR

IInference
- **TF1Inference**
- **TF2Inference**
- **PyTInference**

PyTorch PyTInference

TensorConversion
- Tensor2PyTTensor

Input model information
- Conversion correct shape
- Conversion data type

USER

Model
Mask RCNN
BLM detector

TensorConversion
- PyTtensor2Tensor