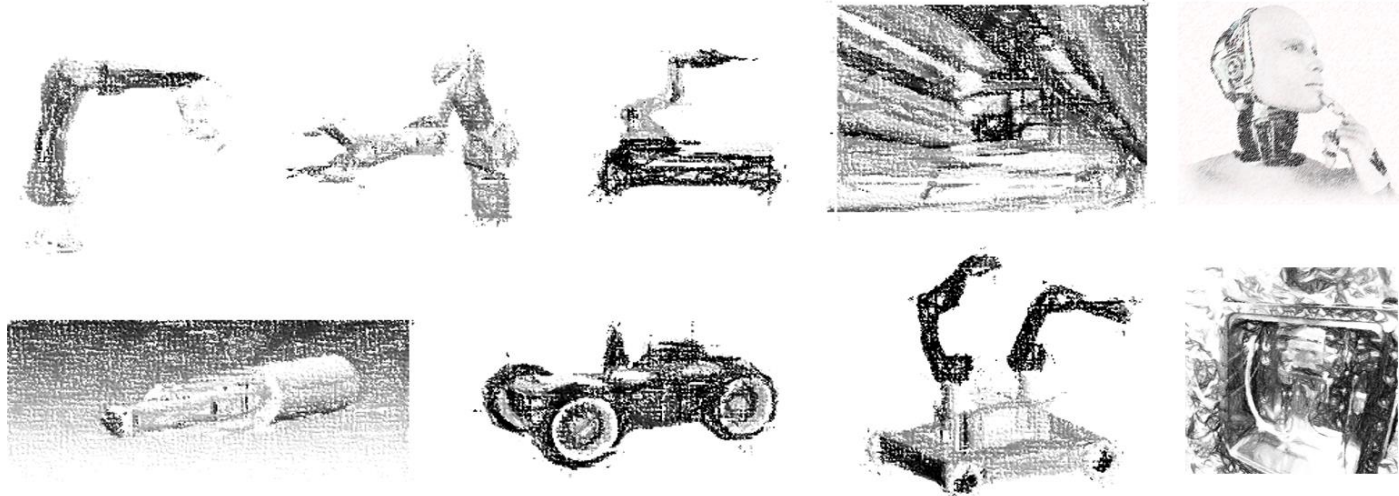


Robotic Solutions for CERN Accelerator Harsh Environments

Mario DI CASTRO
EN-SMM



ENGINEERING
DEPARTMENT

EP-DT Technical Seminar, 21st May 2019

Contents

- Introduction to Robotics
- Needs and Challenges for Robotic Solutions
- Operational Systems
- R&D and Artificial Intelligence
- Conclusions

Robotics

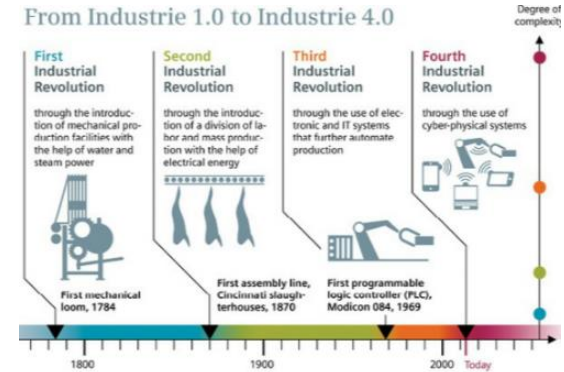
➤ Industry 4.0

- ✓ Robots
- ✓ Artificial intelligence
- ✓ Internet of things
- ✓ Diffuse signals
- ✓ Sensor fusion
- ✓ Simplification in the use of robots

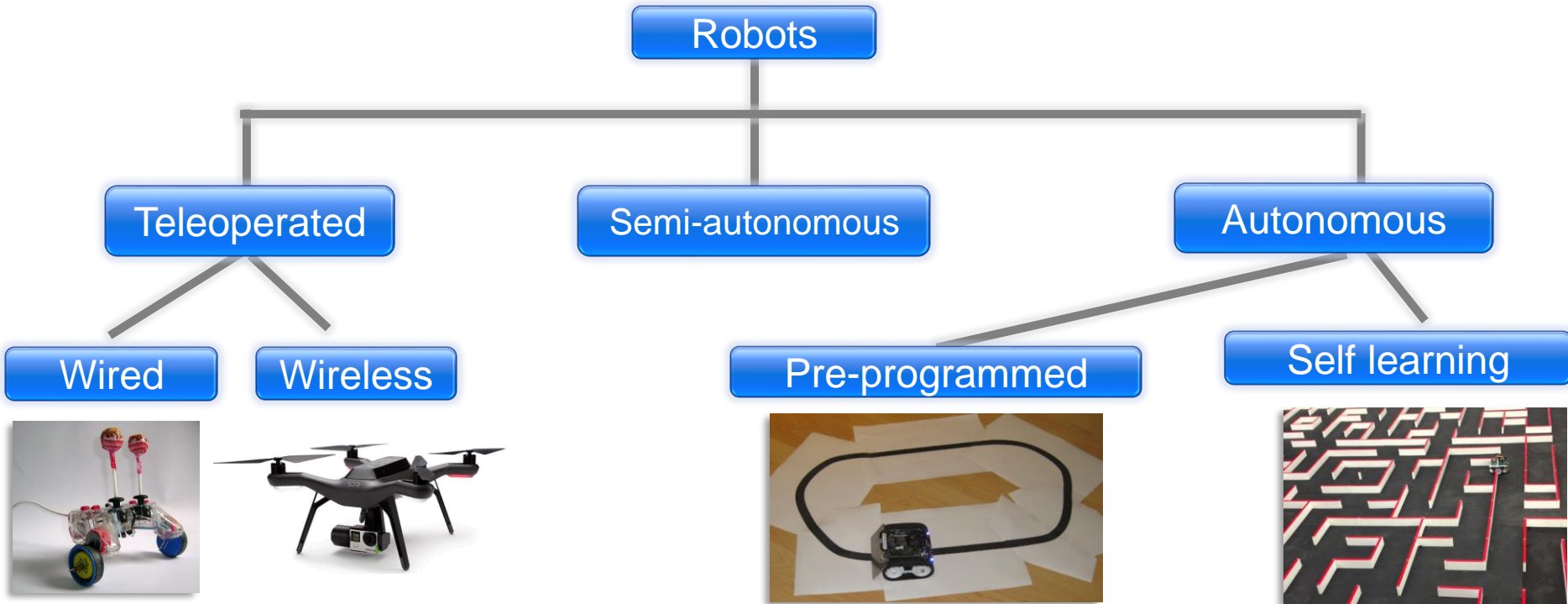
➤ Human-robot cooperation

- ✓ ISO 2011
- ✓ Robots can assist humans
- ✓ Robot learning by demonstration

From Industrie 1.0 to Industrie 4.0

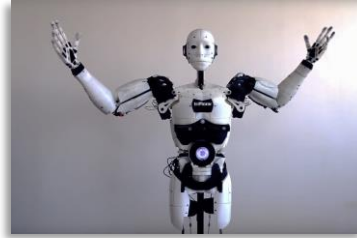


Robotics: type of robots (based on controls)



Robotics: type of robots (based on application)

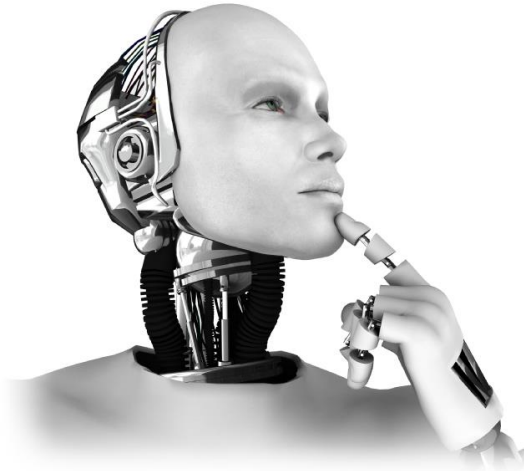
- ✓ Hobbies, competition and entertainment
 - ❑ Suitable for high school teaching
- ✓ Industrial
 - ❑ Repetitive tasks
- ✓ Medical
 - ❑ Surgery/Rehabilitation
- ✓ Domestic or household
- ✓ Military
- ✓ Service and space robot
 - ❑ Research
 - ❑ Intelligent



Artificial Intelligence

➤ Intelligence exhibited by machines [1] [2]

- ✓ Localization
- ✓ Knowledge
- ✓ Learning
- ✓ Planning
- ✓ Decision making
- ✓ Perception/Sensing



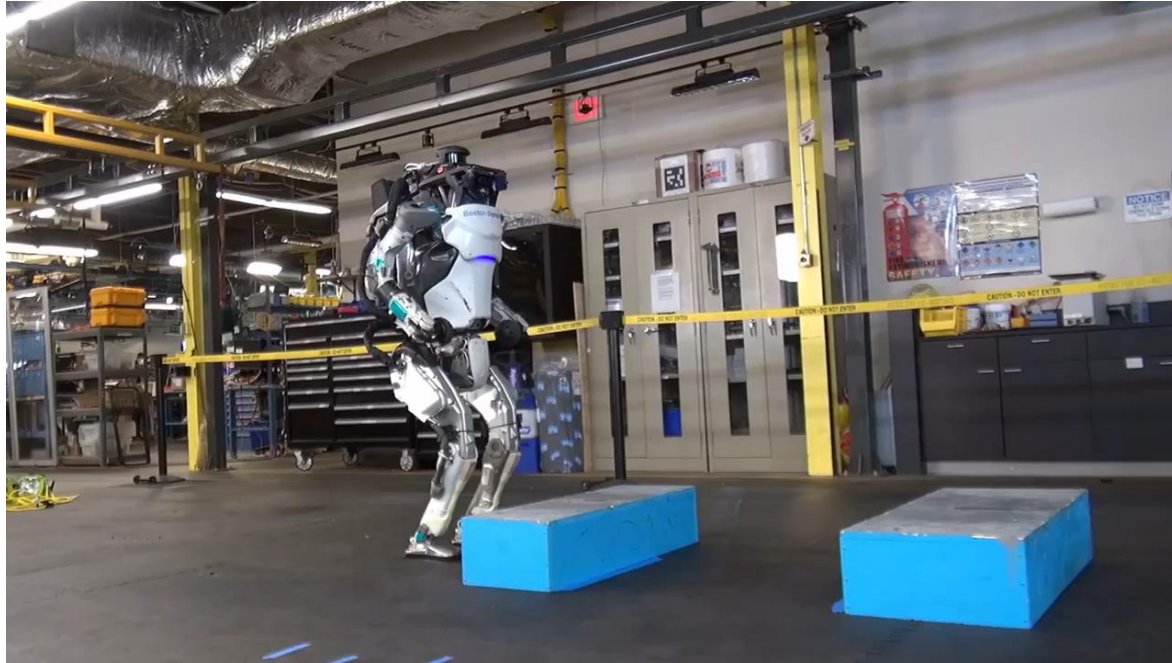
Robots made in Hollywood

iRobot, Chicago 2035



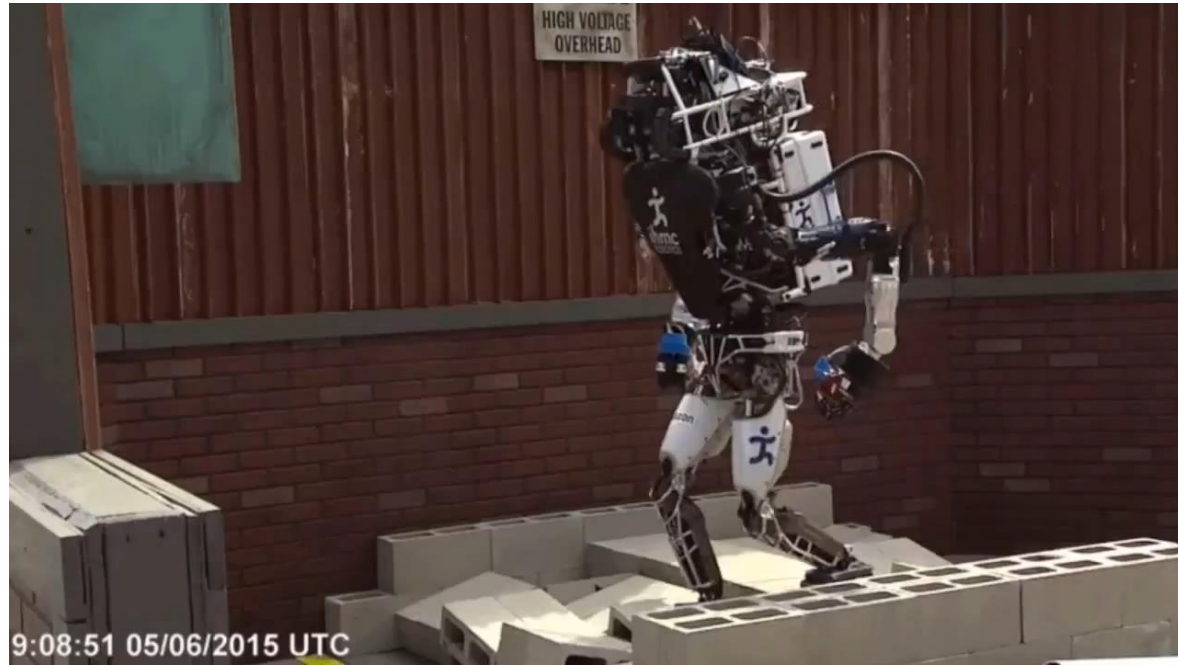
Robots made by *Boston Dynamics*

A mystery for the robotic community



Robots in reality (R&D)

DARPA Robotics Challenge [5]



Robots in reality (field robotics)

✓ Inspection robots

- ✓ Snake robots
- ✓ Oil and gas industries to inspect pipes and tanks



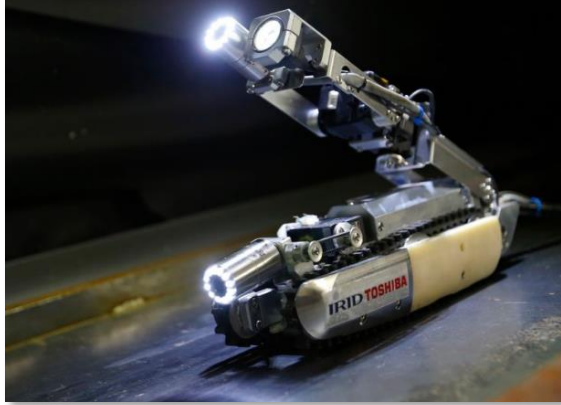
✓ Telemanipulators

- ✓ Nuclear decommissioning



Robots in reality (field robotics)

- The only reliable robotic solutions exist in industry for repetitive tasks
- Plenty of ideas and prototypes coming from university, but none of them work reliably for harsh and unstructured environments
- ✓ At Fukushima, no robot has been capable of safely inspecting the zone and returning to the base [6]



Robotics

➤ Ethical aspects [3] [4]

- ✓ Will robots replace humans?
- ✓ Will robots take our jobs?
- ✓ Will robots make humans unnecessary?
- ✓ Is humanity just a phase in a robotic evolution?



Robotics

- There is a lot of potential in this technology to be beneficial for people
- Ultimately, everything depends on how we decide to use the technology

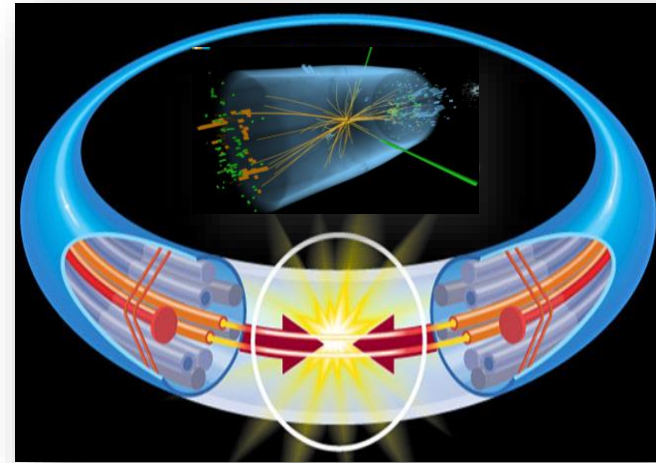


Robots must improve the quality of work by taking over dangerous, tedious and dirty jobs that are not possible or safe for humans to perform

Robotics mandate at CERN

- The “mission” of tele-robotics at CERN may be resumed in the following:

Ensuring safety of Personnel
improving availability of CERN’s accelerators

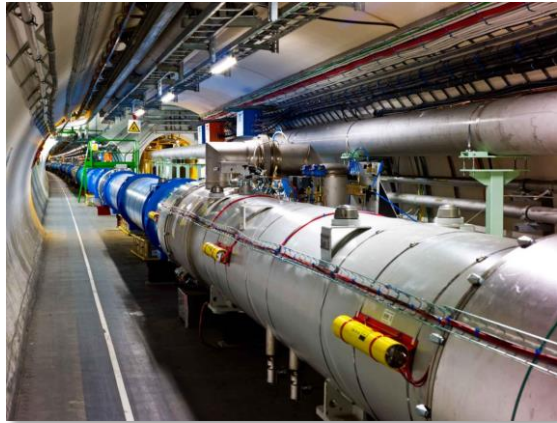


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Needs for Mechatronics/Robotics at CERN

- Control, inspection, operation and maintenance of radioactive particle accelerators devices
- Experimental areas and objects not built to be remote handled/inspected
 - ✓ Any intervention may lead to “surprises”
 - ✓ Risk of **contamination**



The LHC tunnel



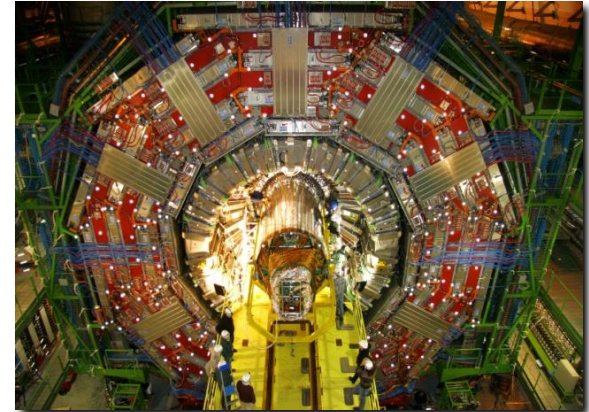
North Area experimental zone



Radioactive sample handled by a robot

Difficulties for tele-robotics at CERN

- Radiation, magnetic disturbances, delicate equipment not designed for robots, big distances, communication, time for the intervention, highly skilled technicians required (non robotic operators), etc.



Challenges for robotic solutions @ CERN

- Design of new equipment has however to keep in mind our goals:

- ✓ Safety of Personnel
- ✓ Maximize availability



- We cannot risk that a robot stops in the middle of the accelerator, or provokes an accident heavier than the problem it is trying to solve
- Risk analysis and recovery scenarios in the implementation of robotic solutions comes before any decision for the intervention

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Object Detection and Recognition for Teleoperation #1

- Teleoperation is strongly increased during the last years at CERN [7]



Telemax robot



EXTRM robot with single arm (CERN made)



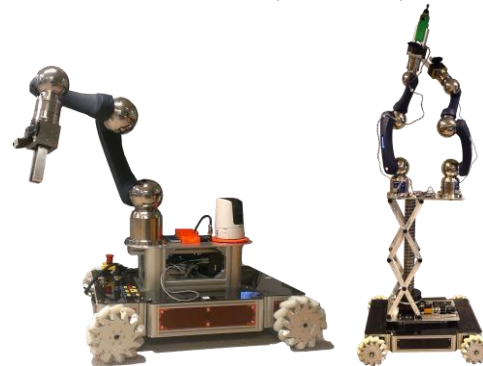
The TIM (CERN made)



Teodor robot



EXTRM robot (CERN made)



CERNbot (CERN made)



CRANEbot (CERN made)

Object Detection and Recognition for Teleoperation #1

- Teleoperation is strongly increased during the last years at CERN [5] [19-22]

More than 30 robots in operation

- AUTONOMOUS INSPECTIONS
- OPERATOR DRIVEN INSPECTION
- ASSISTED INSPECTION
- TELEOPERATIONS
- ASSISTED TELEMANIPULATION
- AUTONOMOUS REMOTE OPERATION
- SAFETY, SEARCH AND RESCUE

STRONG MAINTENANCE AND UPGRADE PROGRAM
DEPENDING ON HOW MUCH THE ROBOTS ARE USED
AND HOW THEY ARE MADE



Telemat



Teodor robot



EXTRM robot (CERN made)

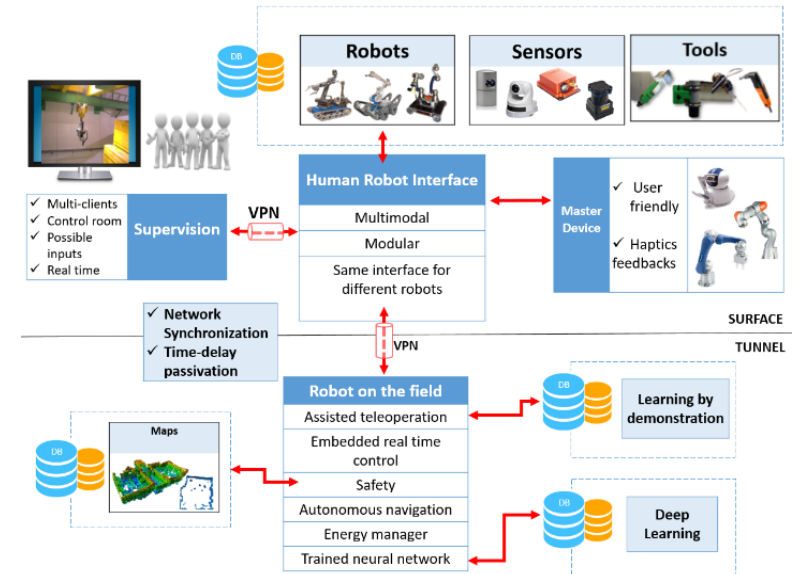
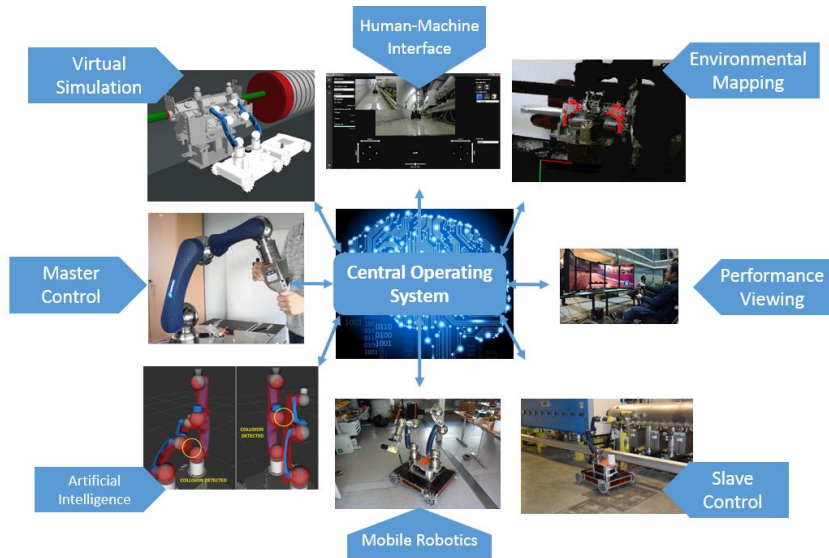
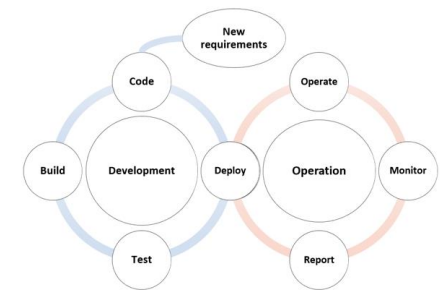


CERNbot (CERN made)

CERNbot (CERN made)

CERNTAURO Framework

- In house robotic control system [7]
- No use of commercial solutions [8]
- Operate all CERN robots
- Sensor acquisition, fusion, measurements etc.



CERNTAURO framework

Mechatronic System

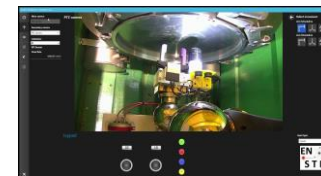


← Perception

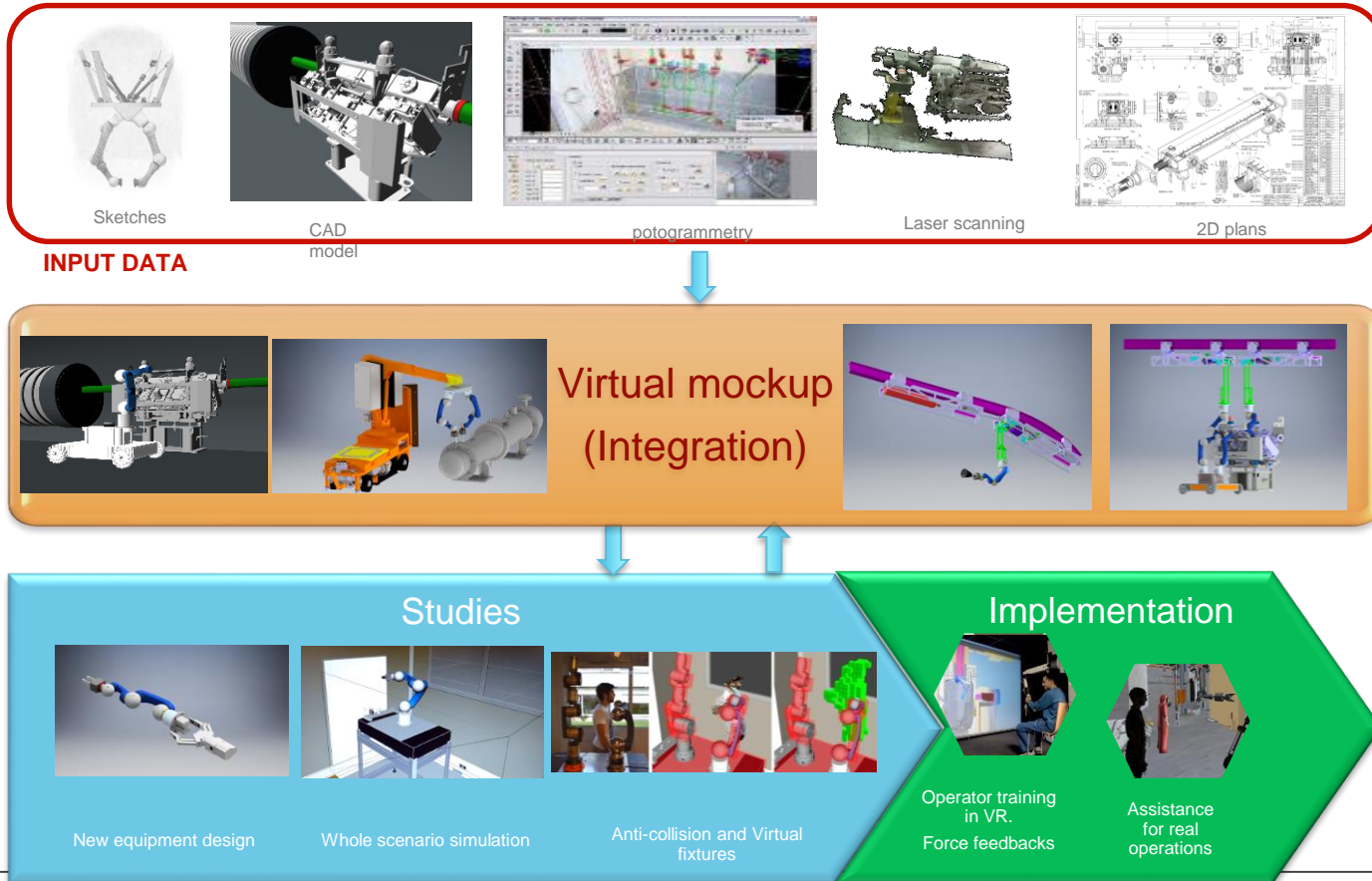
← Actuation

← Motion

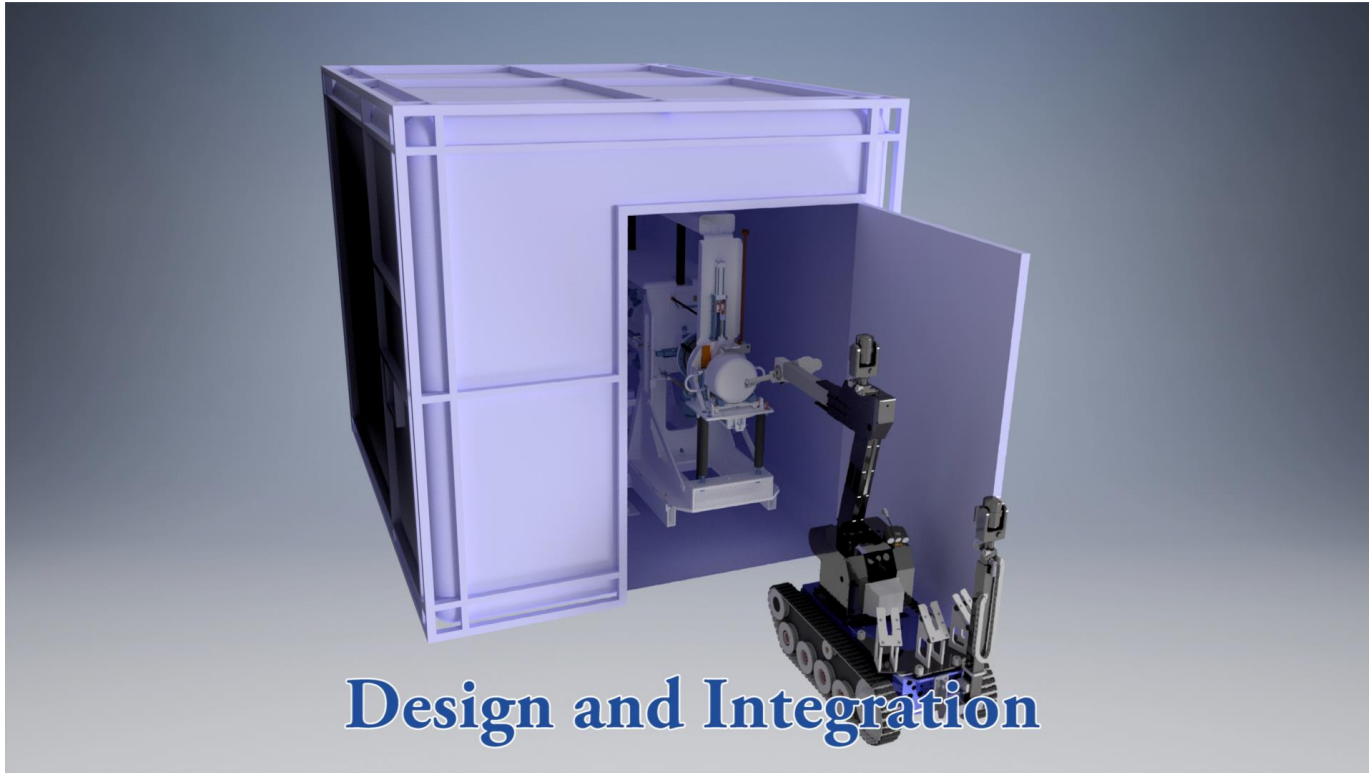
- **New robot and robotic control developed [9]**
 - ✓ Human robot interface
- **New user-friendly bilateral tele-manipulation system**
 - ✓ Haptic feedback
 - ✓ Assisted teleoperation
- **Artificial intelligence**
 - ✓ Perception and autonomy
 - ✓ Deep learning
- **Operator and robot training system**
 - ✓ Virtual and augmented reality
 - ✓ Learning by demonstration



VERO: Virtual Environment for intelligent Robotic Operations



Robotic Activities in EN-SMM

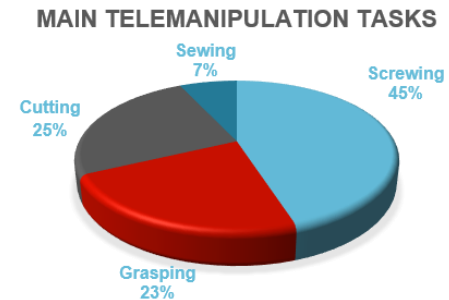
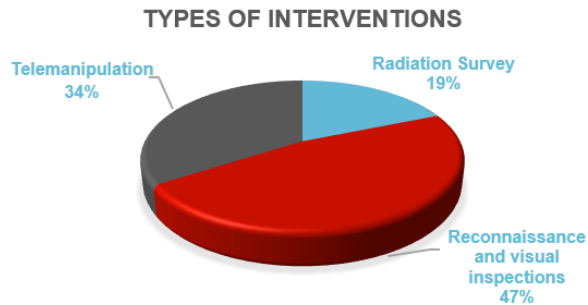


Robotic Support at CERN

Nr. of Interventions in the last 40 months	Nr. of tasks performed in the last 40 months	Robot operation time in harsh environment [h]	Dose Saved [mSv]
135	250	~ 300	~ 120*

* Calculated on human intervention time

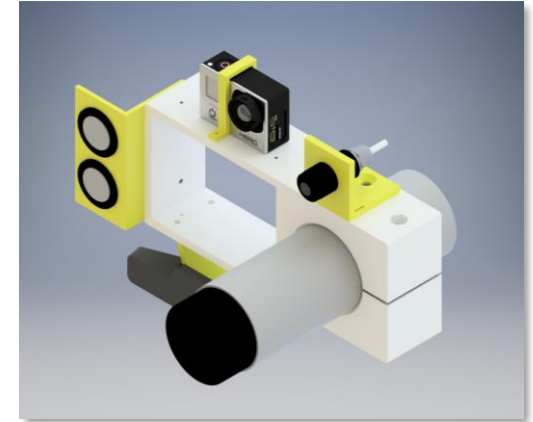
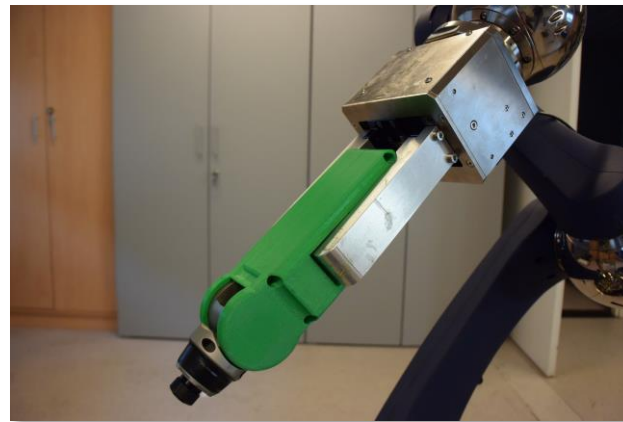
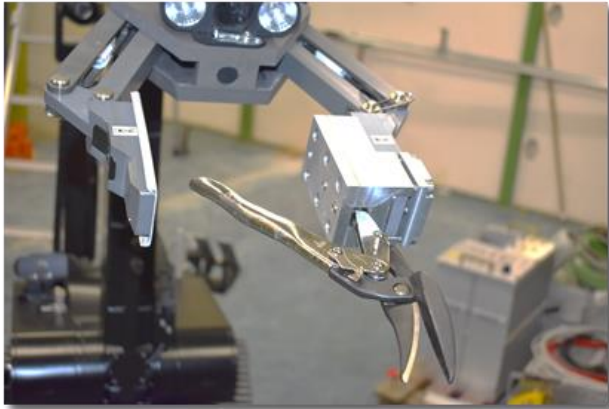
60 % of the interventions were unforeseen and done with very short preparation time



Best practice for equipment design and intervention

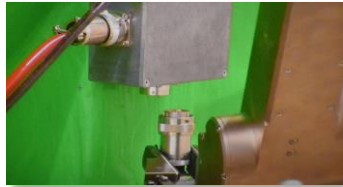
Importance of the design phase, procedures and tools

- Intervention **procedures and tools** are important as the robot/device that does the remote intervention
 - ✓ HL-LHC WG, **ITHACA** - InTerventions in Highly **ACT**ivated **ARE**as in HL-LHC
 - ❑ Guidelines for equipment design and maintenance best practice to reduce personnel radiation exposure.
 - ✓ Taking advantages of robots operational experience for new equipment design (TIDVG, BDF target, AD target, TAXS, TAXN etc.)



Importance of the design phase, procedures and tools

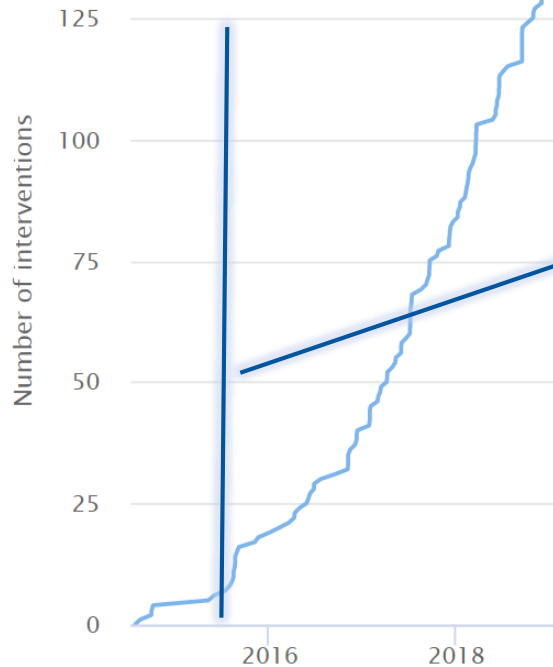
- **Designing** machines that can be maintained by robots using appropriate and easily accessible interfaces will increase the availability and decrease human exposure to hazards



Easier remote or hands-on manipulation than chain-type connection

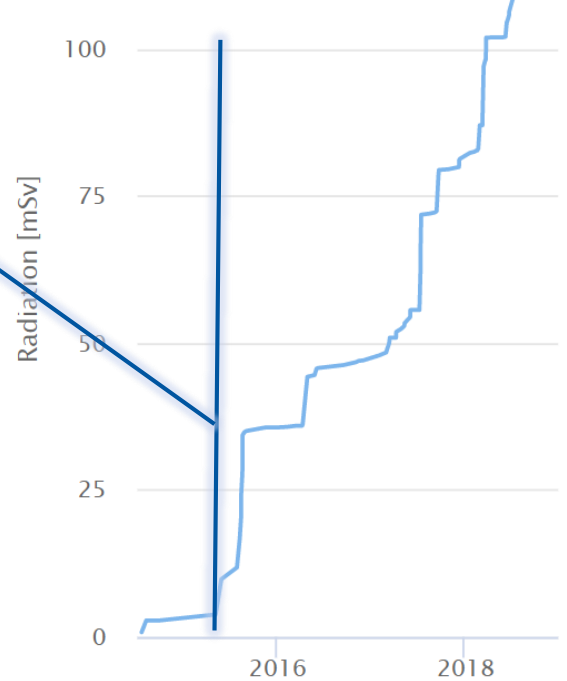
Robotic Support at CERN

Interventions performed



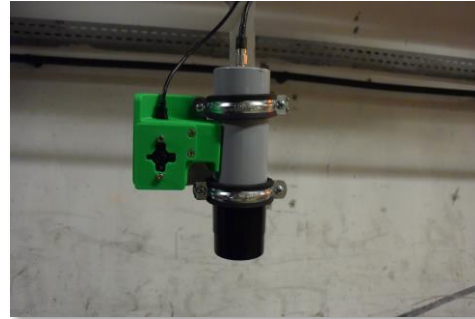
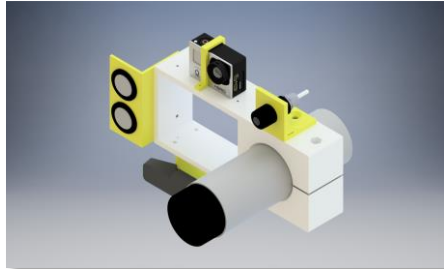
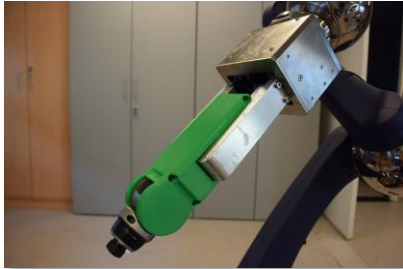
Started to apply CERN custom made robotic solutions. Remote handling capabilities and modularity strongly increased!

Dose saved to personnel



Robotic support in EN-SMM

- **27 intervention mock-ups developed**
 - ✓ 12 “real” and 15 “virtual”
 - ✓ Mockups are extremely useful to develop procedures, tooling, failure mode and recovery scenarios, safety and for operators training
- **More than 50 tools + several procedures and recovery scenarios developed**



Robots at CERN: TIM

Built at CERN, used for inspection, radiation mapping of the LHC and survey. Operational Experience and technology could be useful for general tunnels inspections [10]

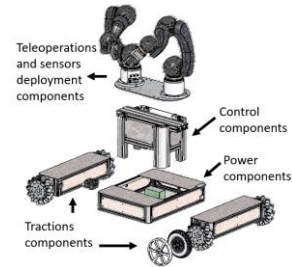
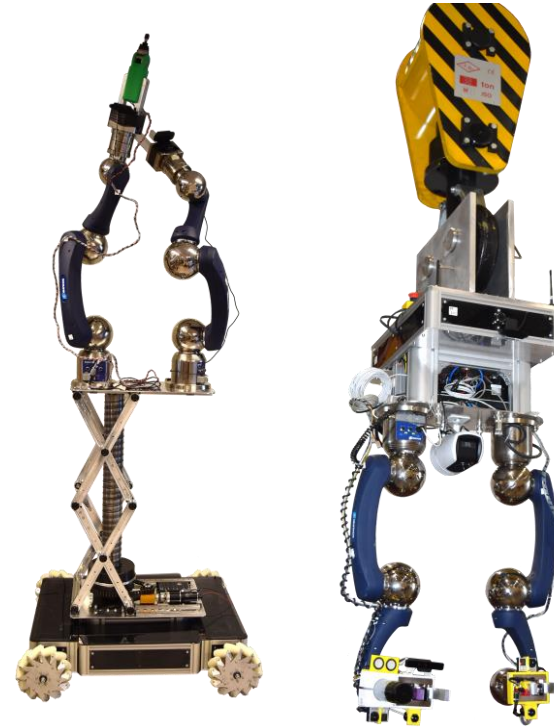


Robots at CERN: TIM

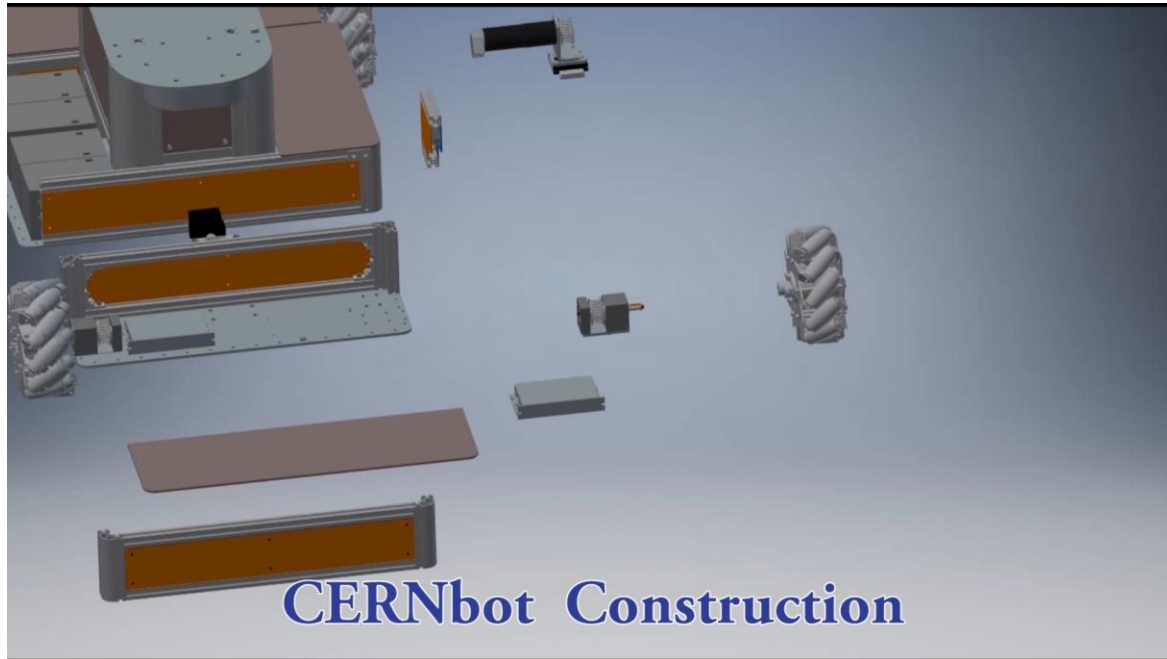


Robots at CERN: CERNbot

Built at CERN, used for inspection, environmental measurements including radiation, teleoperation and in-situ maintenance [11]

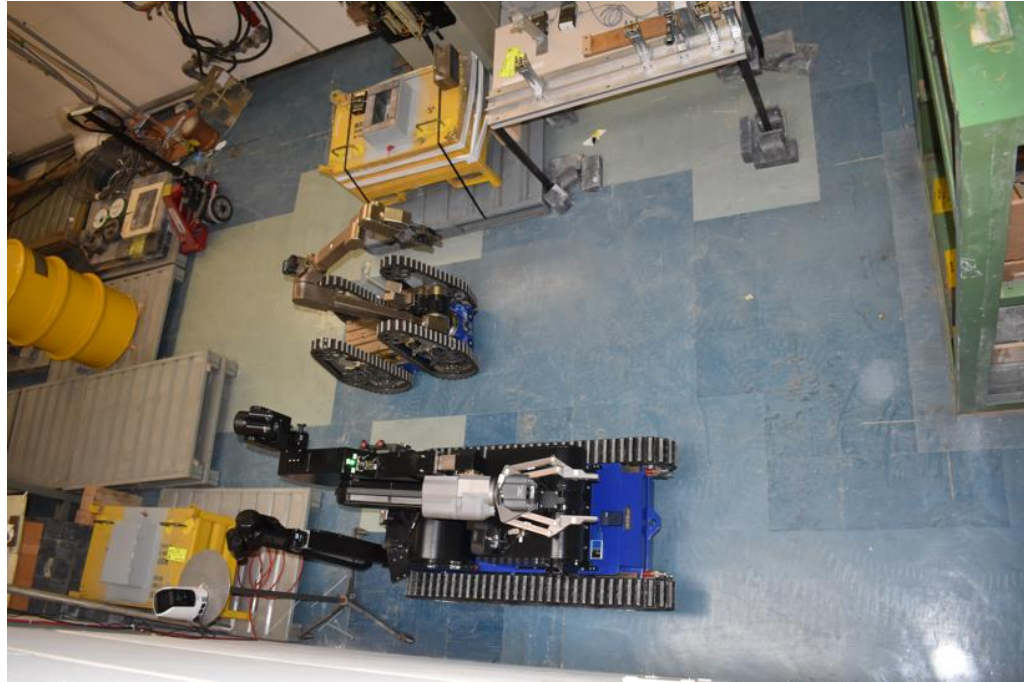


Robots at CERN: CERNbot



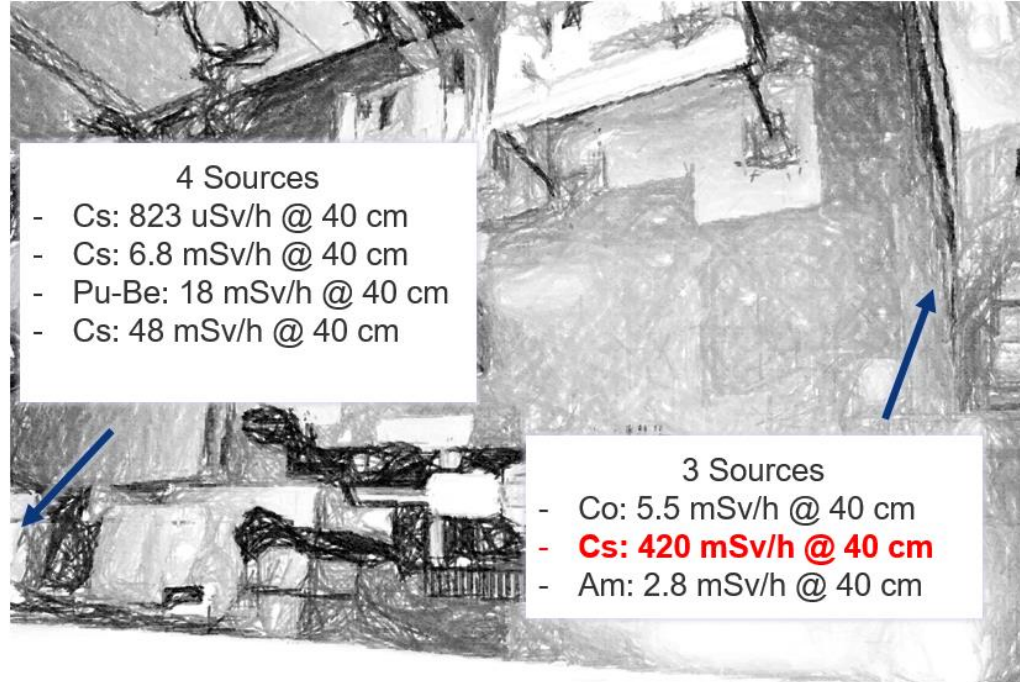
Robots at CERN: Tele-operation and in-situ maintenance

➤ Radioactive sources handling



Robots at CERN: Tele-operation and in-situ maintenance

➤ Radioactive sources handling



Robots at CERN: Tele-operation and in-situ maintenance

➤ Radioactive sources handling



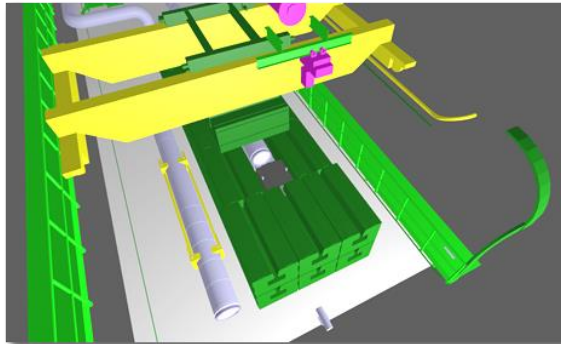
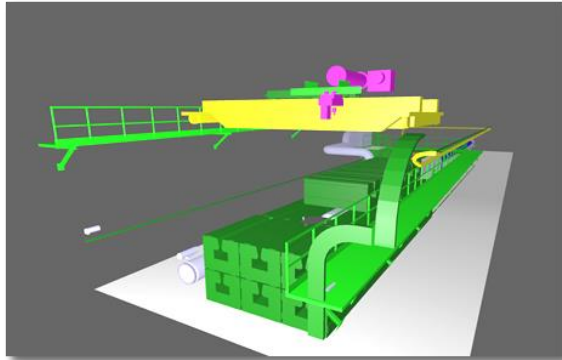
Robots at CERN: Tele-operation and in-situ maintenance

➤ Radioactive sources handling



Intervention Examples

➤ LHC TDE inspection

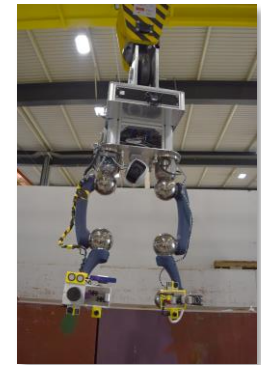
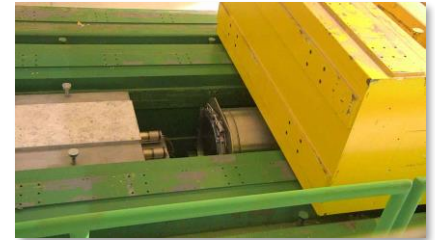
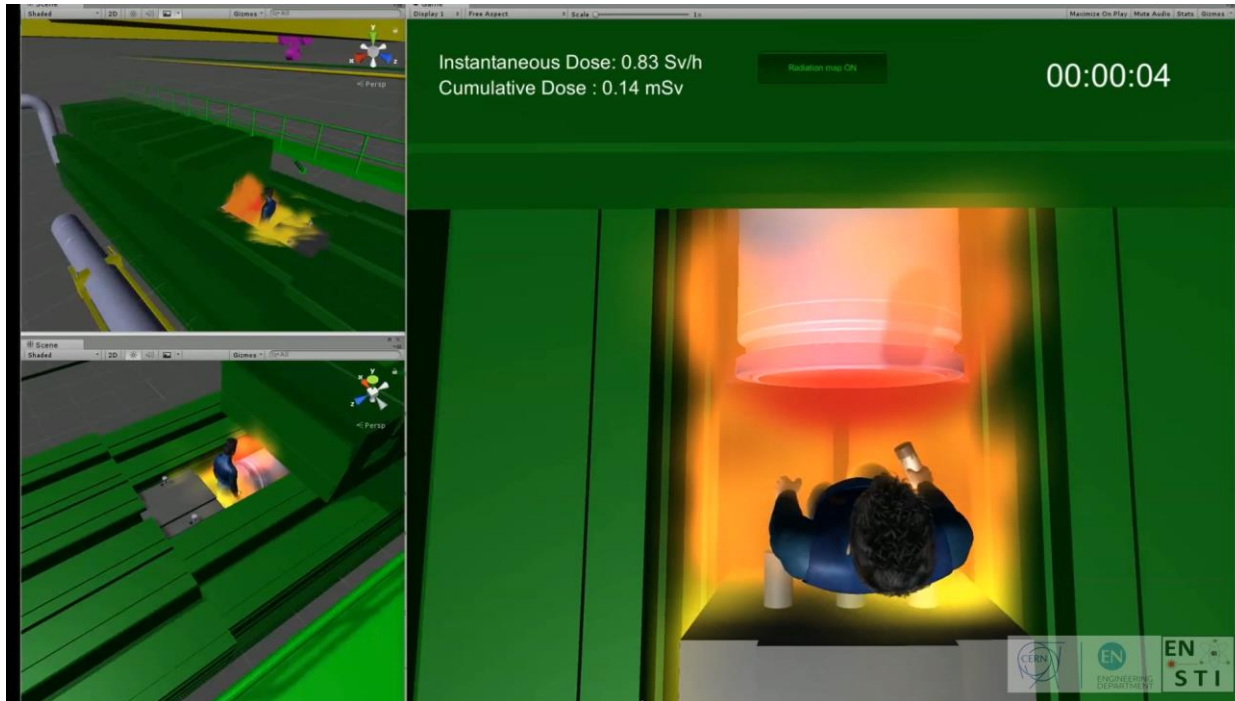


CERNbot v1.0 core



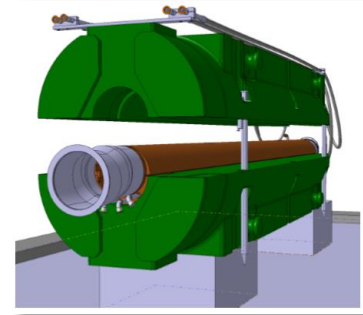
Intervention Examples

➤ LHC TDE inspection



Intervention Examples

- **SPS TIDVG de-installation and inspection on surface**
 - ✓ Environment preparation, teleoperation (disconnections), core visual inspection, vacuum leak detection



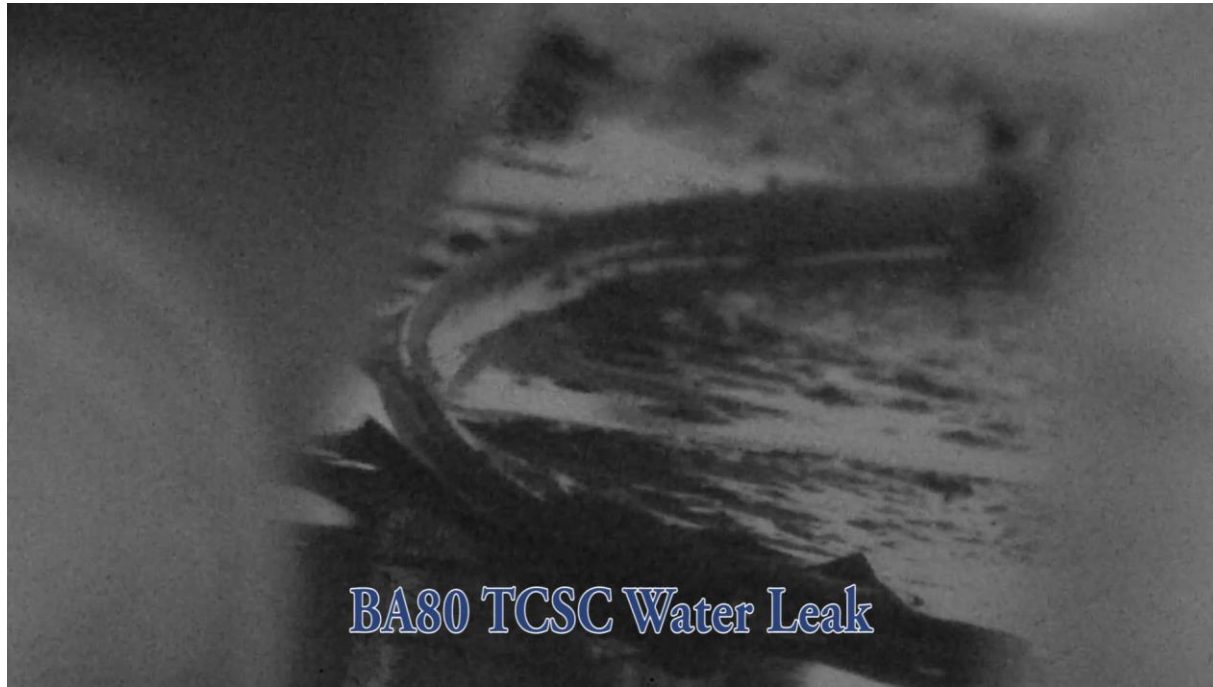
Intervention Examples

- **SPS TIDVG de-installation and inspection on surface**
 - ✓ Environment preparation, teleoperation (disconnections), core visual inspection, vacuum leak detection ...



Intervention Examples

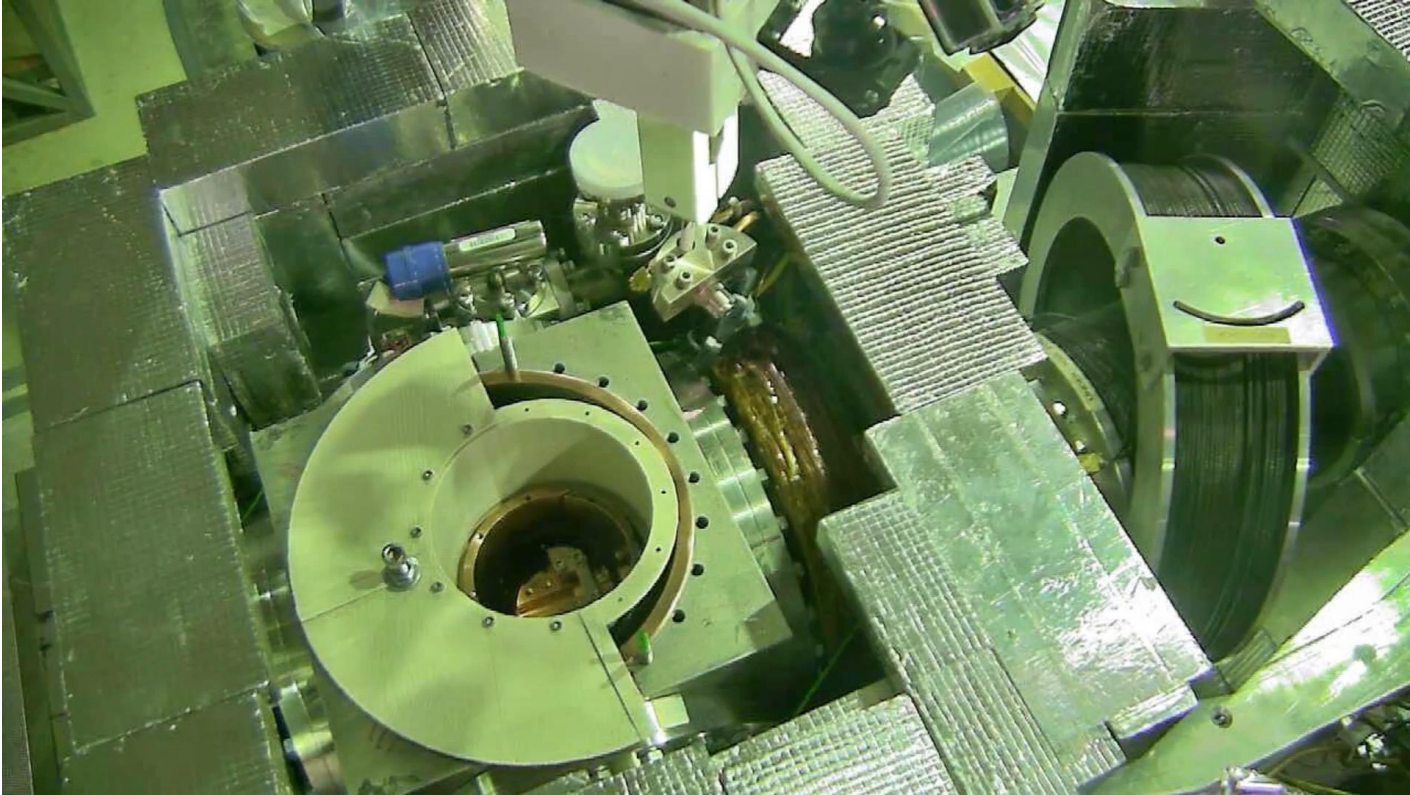
➤ Water leak fix



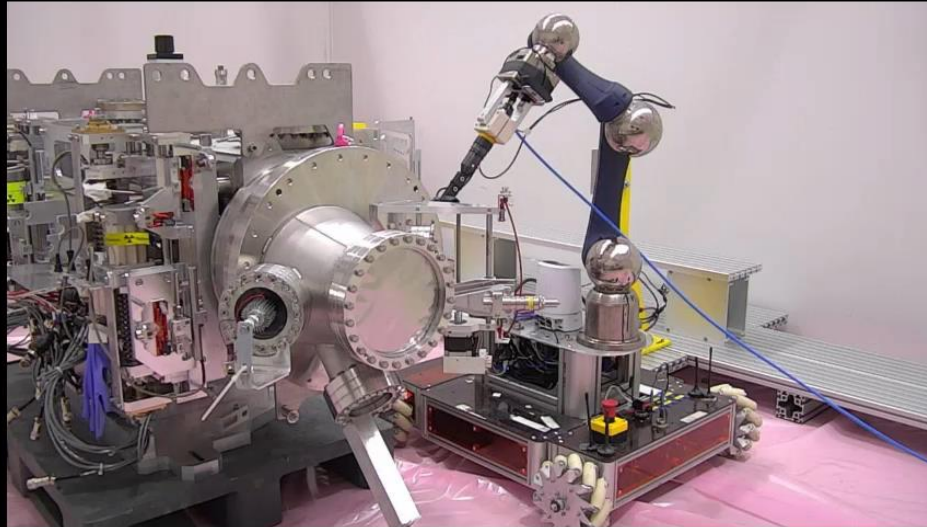
Intervention Examples

AD ATRAP Iridium Source Installation

Intervention Examples



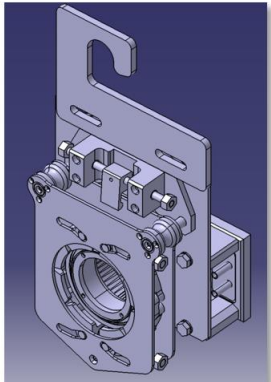
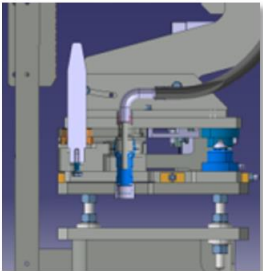
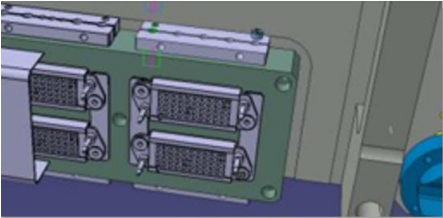
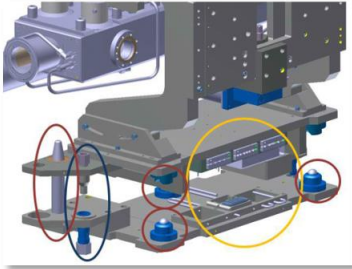
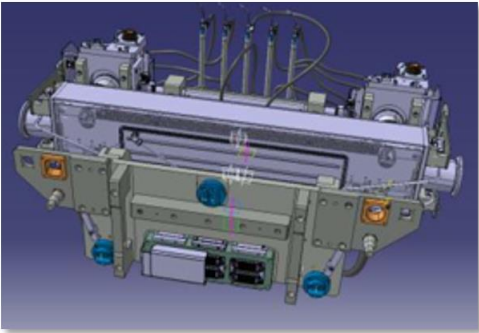
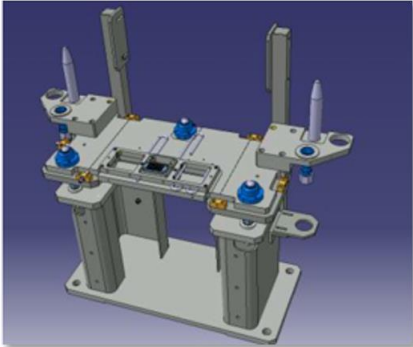
Intervention Examples: HIRADMAT



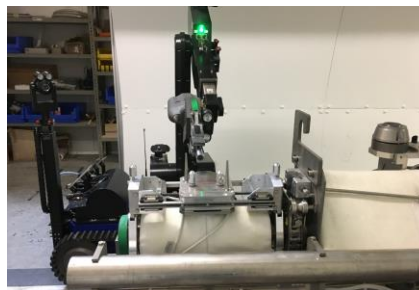
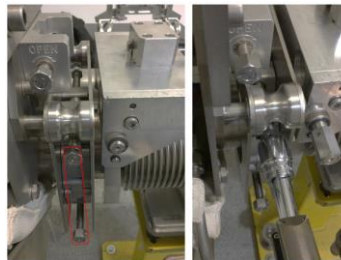
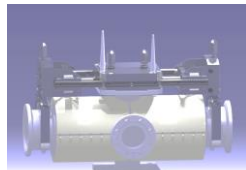
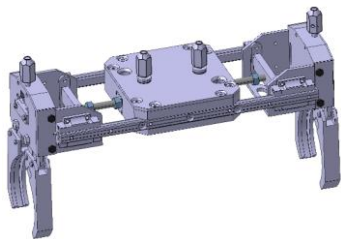
HiRadMat Tank Opening

Existing remote handling compatible solutions (EN-STI)

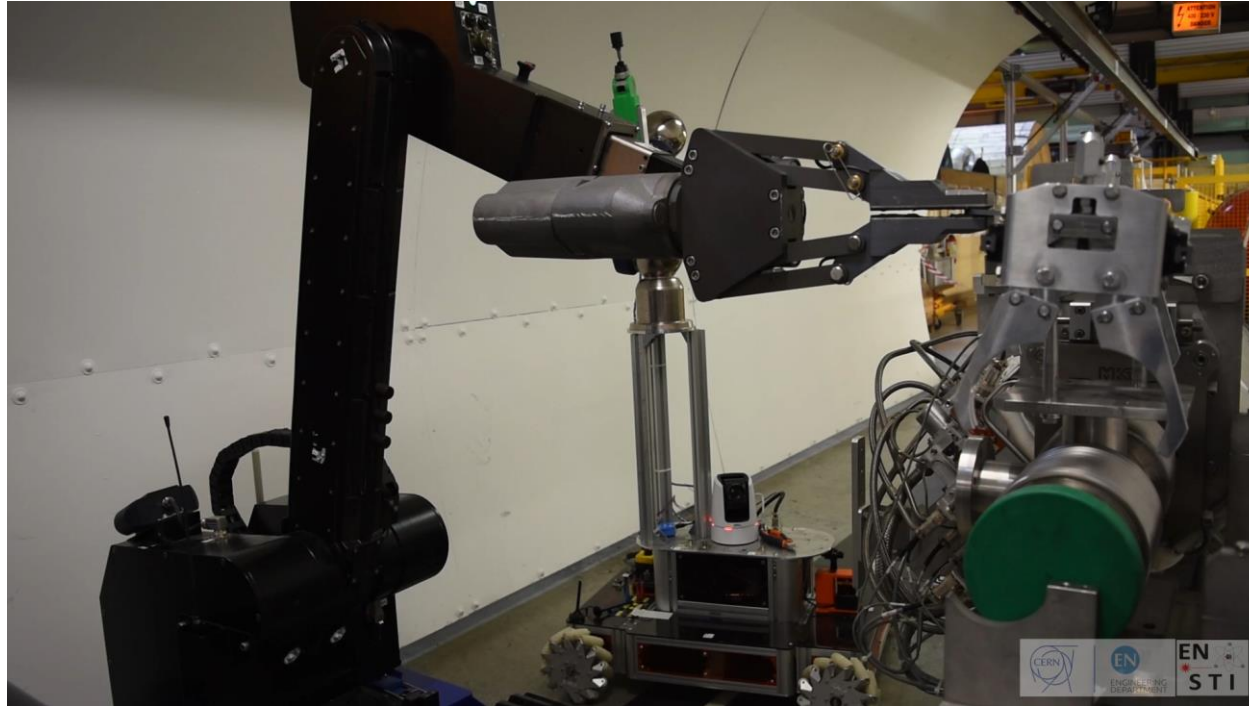
➤ LHC Collimators: plug and play system



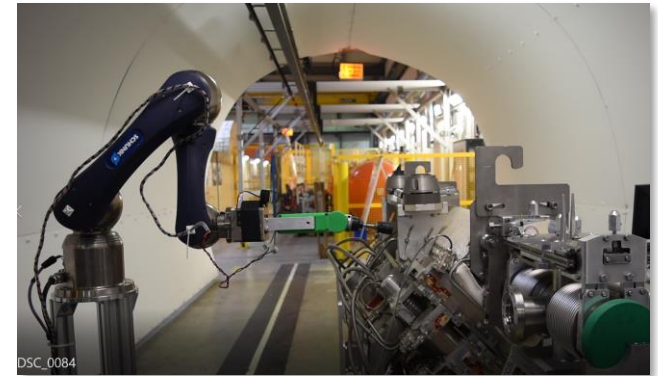
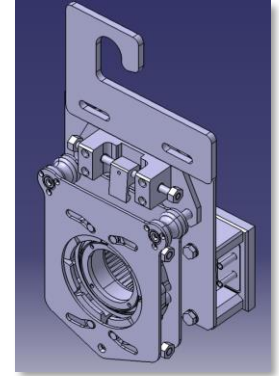
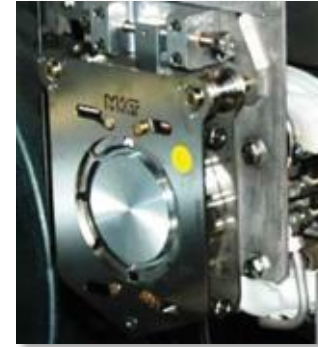
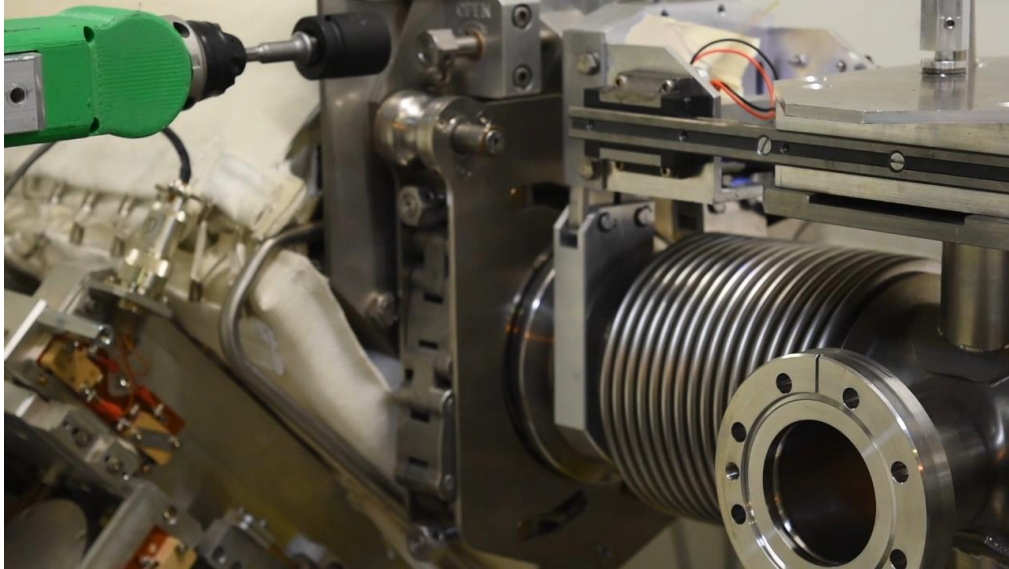
VMTIA maintenance of the LHC Collimators



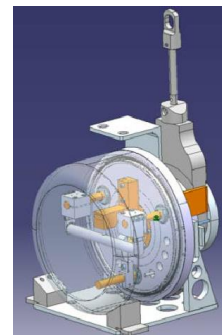
VMTIA maintenance of the LHC Collimators



Opening of the quick vacuum flange using robots

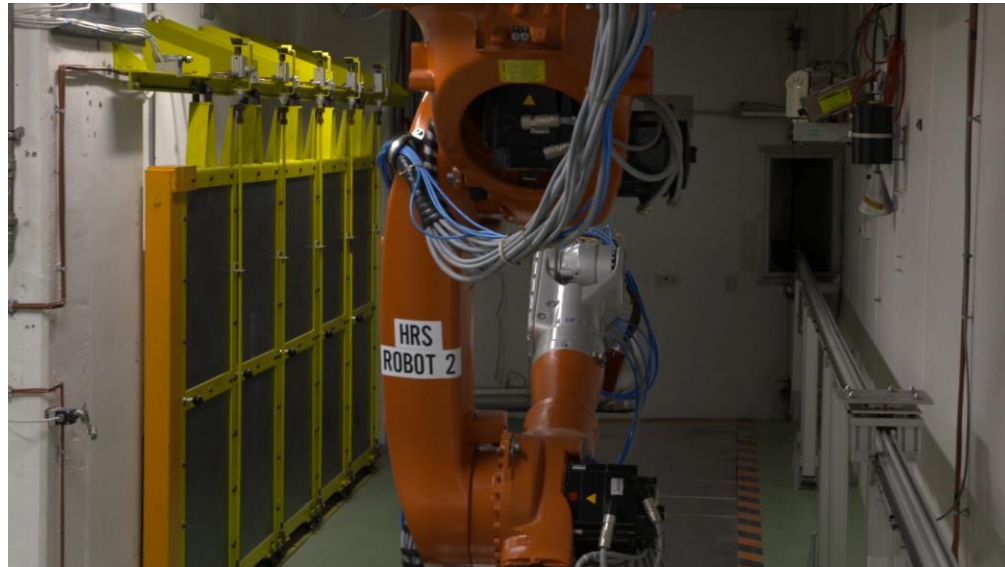
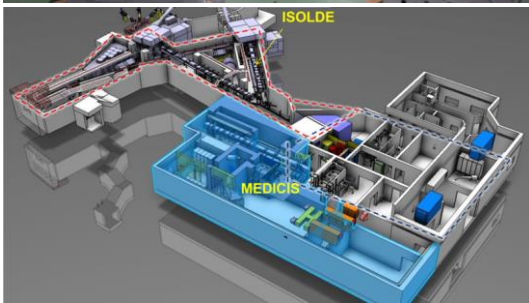


Robots at CERN: Industrial robots



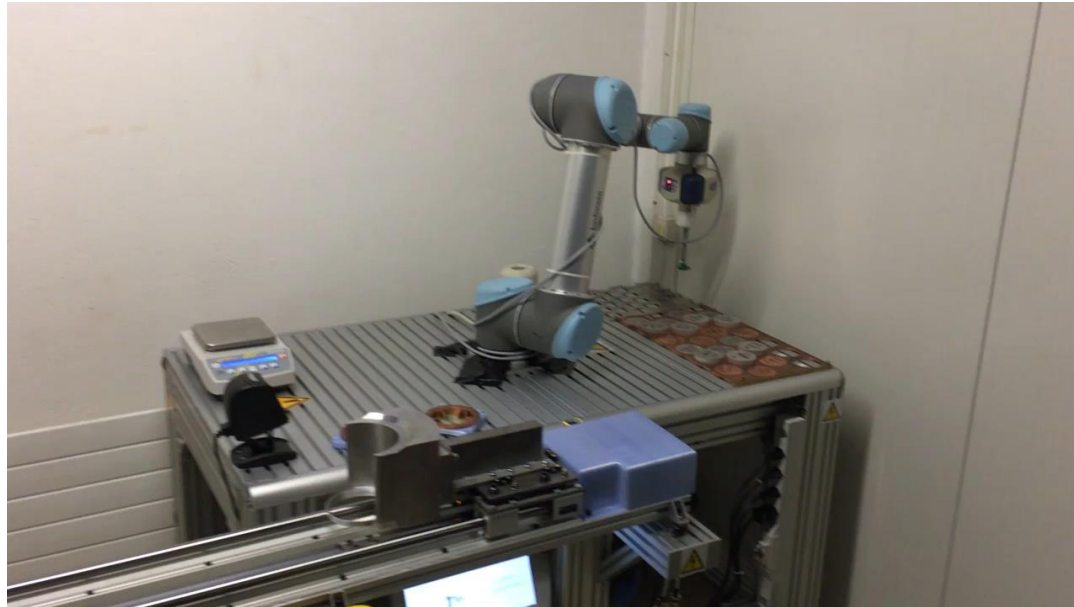
➤ Industrial robots @ ISOLDE and MEDICIS

- ✓ Kuka Manipulators for repetitive pre-programmed tasks



Robots at CERN: repetitive tasks

- **Robotic sample exchanger for automatic spectroscopy of radioactive samples**

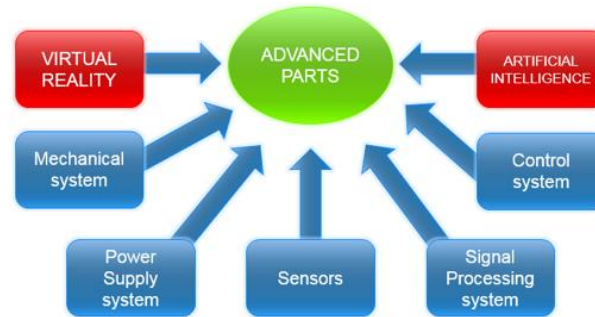


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Research and Developments

- OUR R&D covers all the fundamental blocks of a robotic systems



OPERATION IN UNSTRUCTURED AND HARSH ENVIRONMENT

Development of novel procedures and recovery scenarios setting the bases for a remote handling code of practice in hazardous environments

Virtual and Augmented Reality

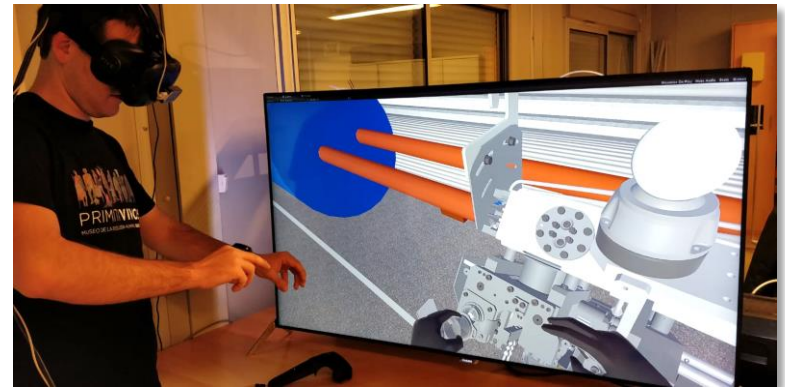
➤ Virtual and augmented reality in EN-SMM needed for:

❑ Simulation of robotic interventions

- ✓ Integration of robots in the environment and choice of robots
- ✓ Intervention procedures
- ✓ Tools design and test
- ✓ Machines risk assessment
- ✓ Robots training by demonstration
- ✓ Operators training
- ✓ Risk analysis
- ✓ Recovery procedures

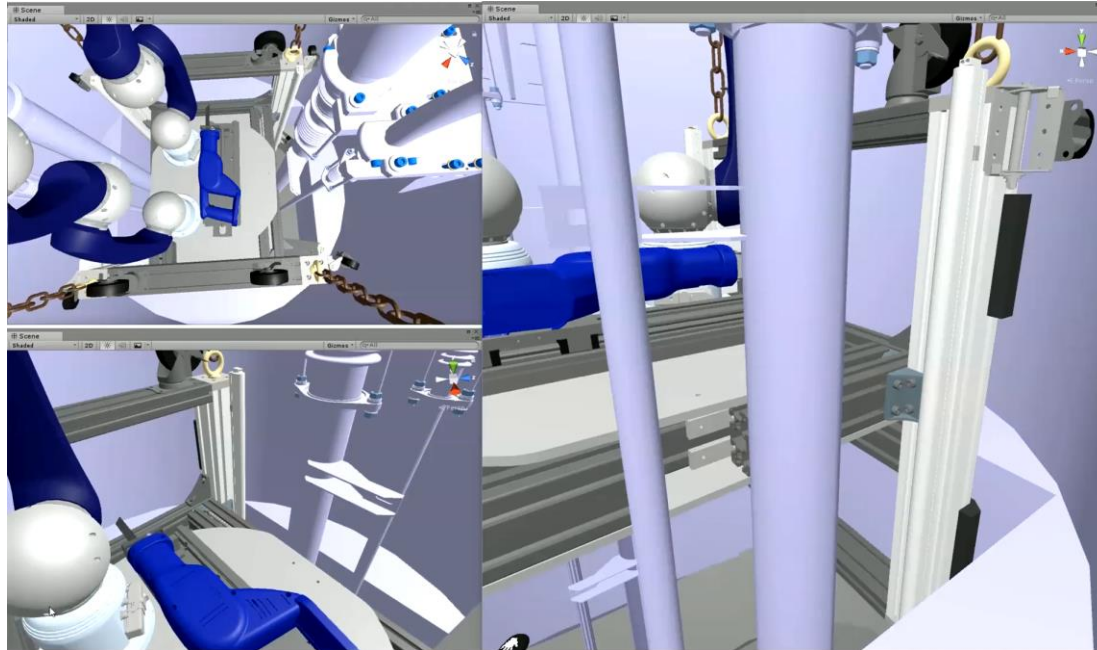
❑ Simulation of human intervention (ITHACA HL-LHC Working group)

- ✓ Human intervention procedures
- ✓ Live radiation levels and cumulated dose while training in VR (Augmented reality in virtual reality)
- ✓ Intervention training
- ✓ Risk analysis



Robotic Intervention Simulation

- Robots integration and task simulation
 - ✓ Procedures, tools design and recovery scenarios

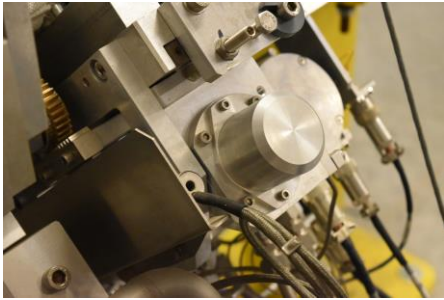


Steering New Machines Design

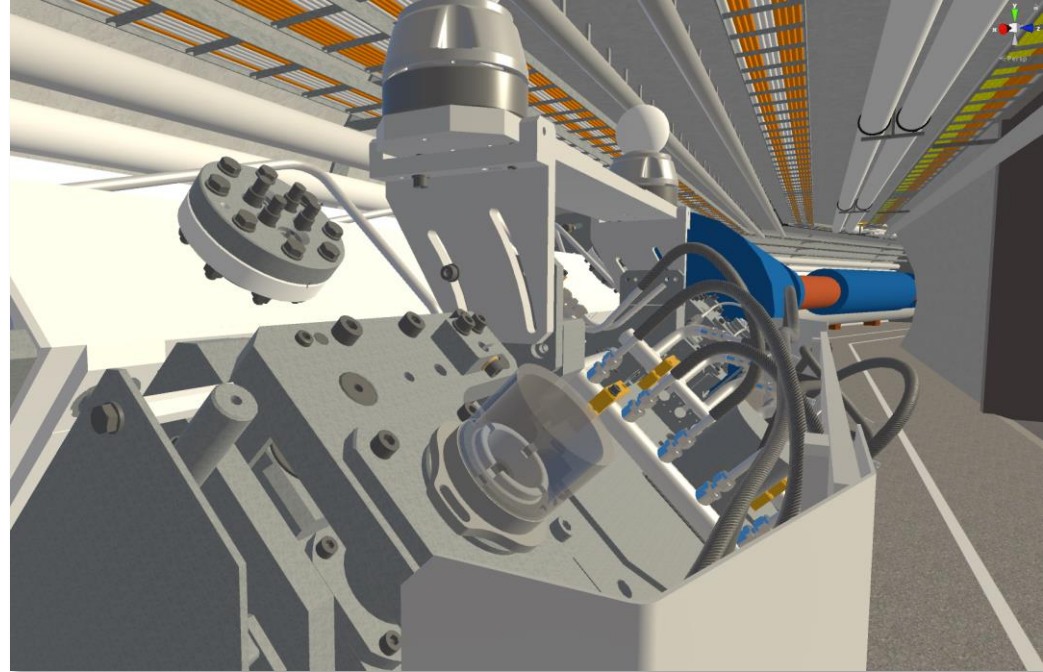
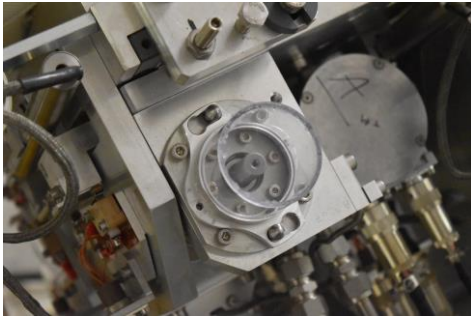
➤ For example, design of the new LHC Collimators motor screw cap

- ✓ Simulation in VR to check hands on handling and “robot friendliness”

Current solution



New solution

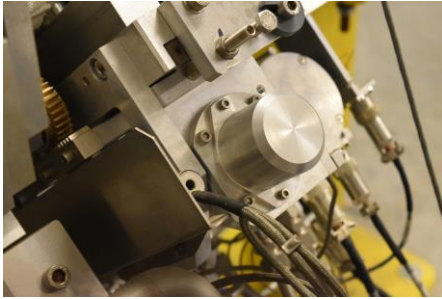


Steering New Machines Design

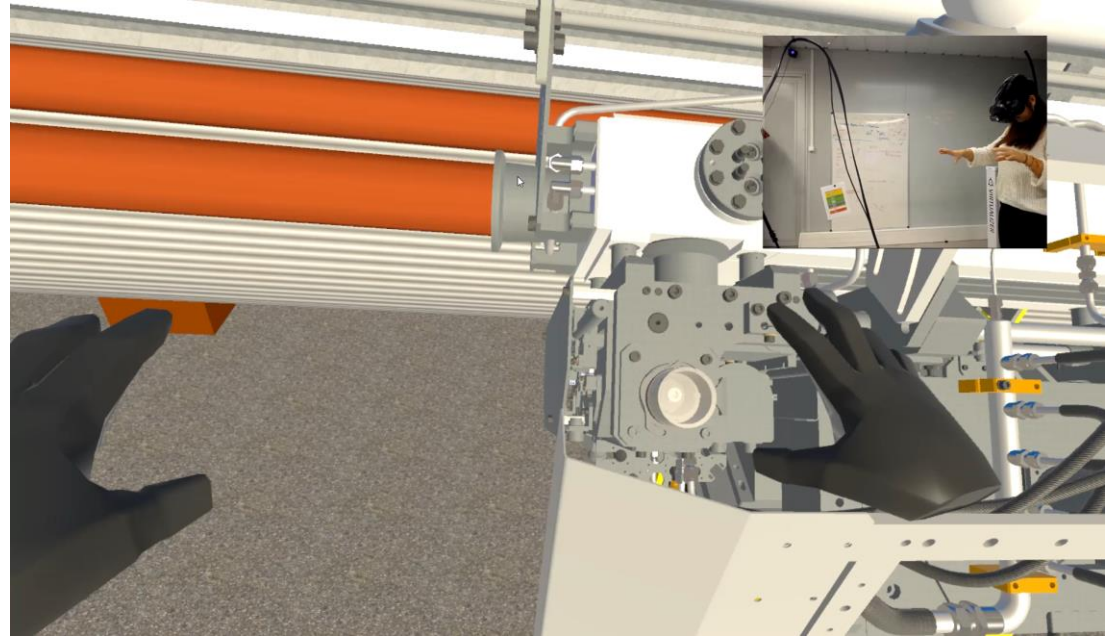
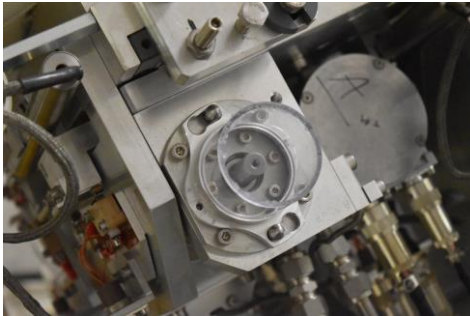
➤ For example, design of the new LHC Collimators motor screw cap

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New solution

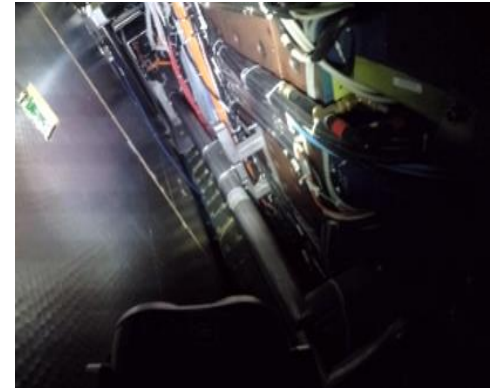
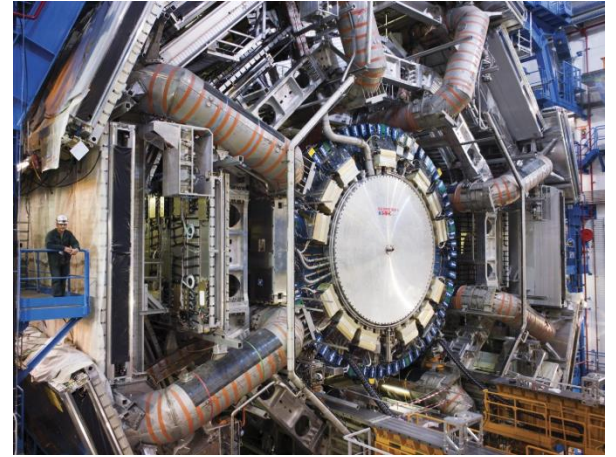


Virtual and Augmented Reality

Train personnel in emergency situation



Virtual Reality



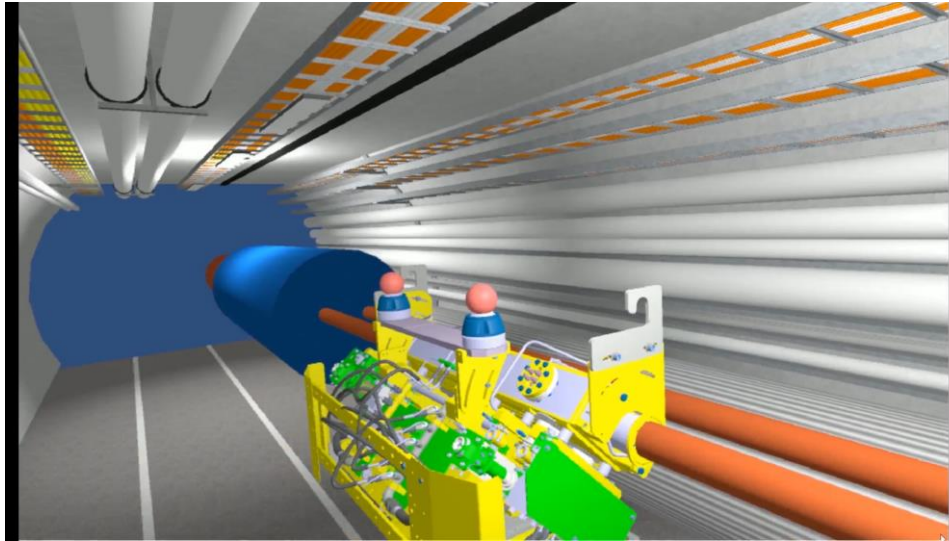
Virtual and Augmented Reality

- For personnel training and risk assessment
- FLUKA/radiation-exposure simulations in VR



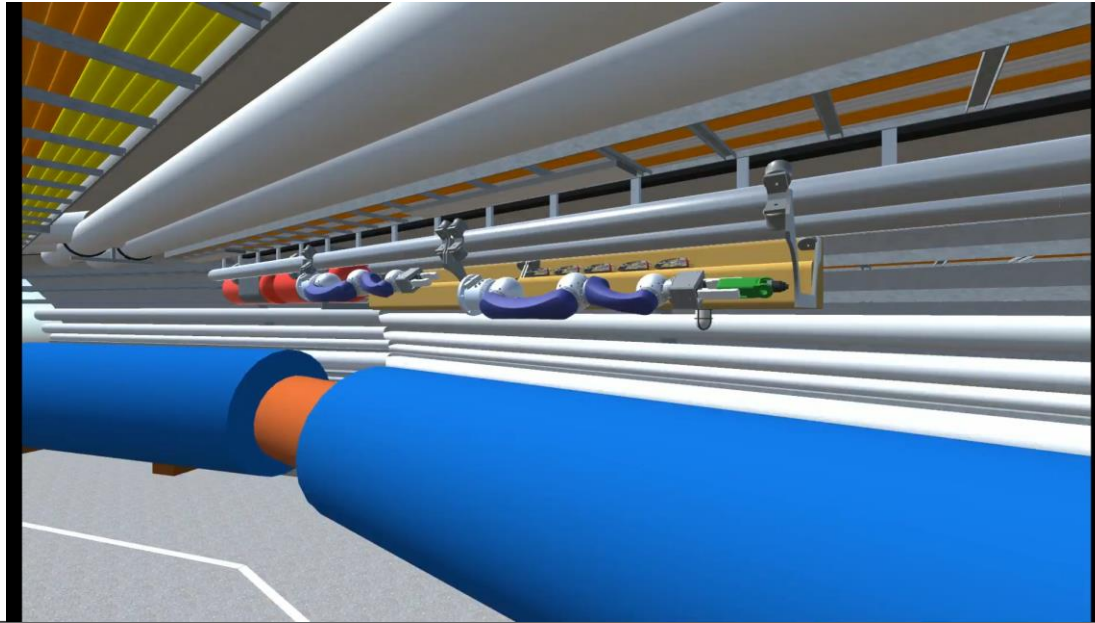
Virtual and Augmented Reality

For Integration, procedures, operator training and operator assistance during teleoperations, in-situ maintenance



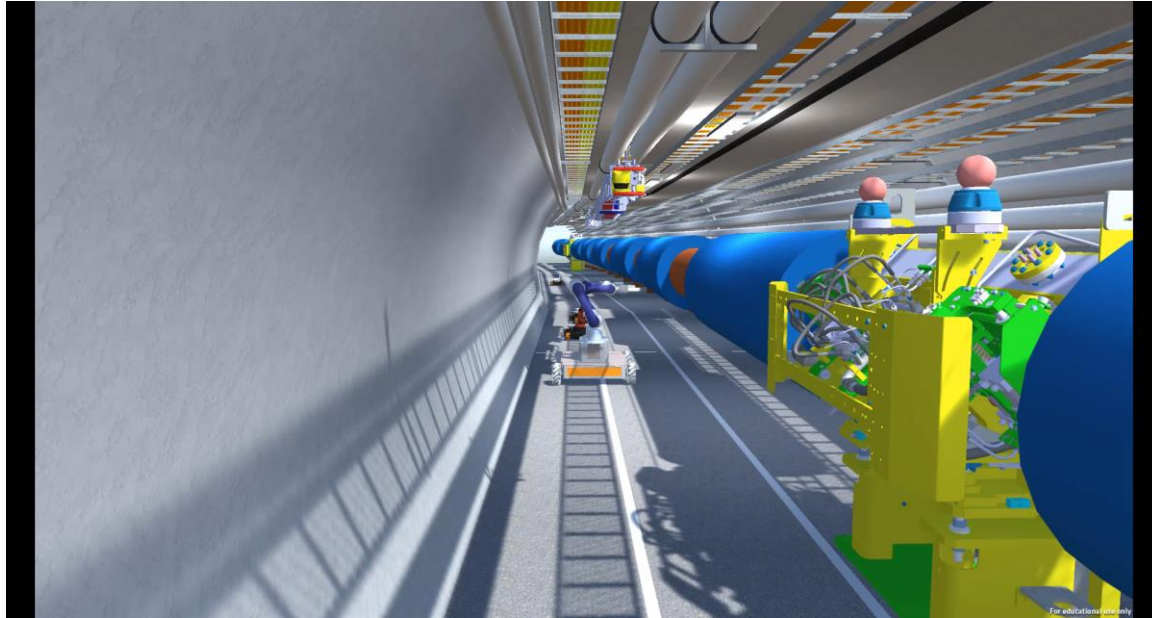
Virtual and Augmented Reality

For Integration, procedures, operator training and operator assistance during teleoperations, in-situ maintenance



Virtual and Augmented Reality

- **Multiple autonomous robot collaborations**
 - ✓ **Several viewing angles for supervision and teleoperation are essentials**

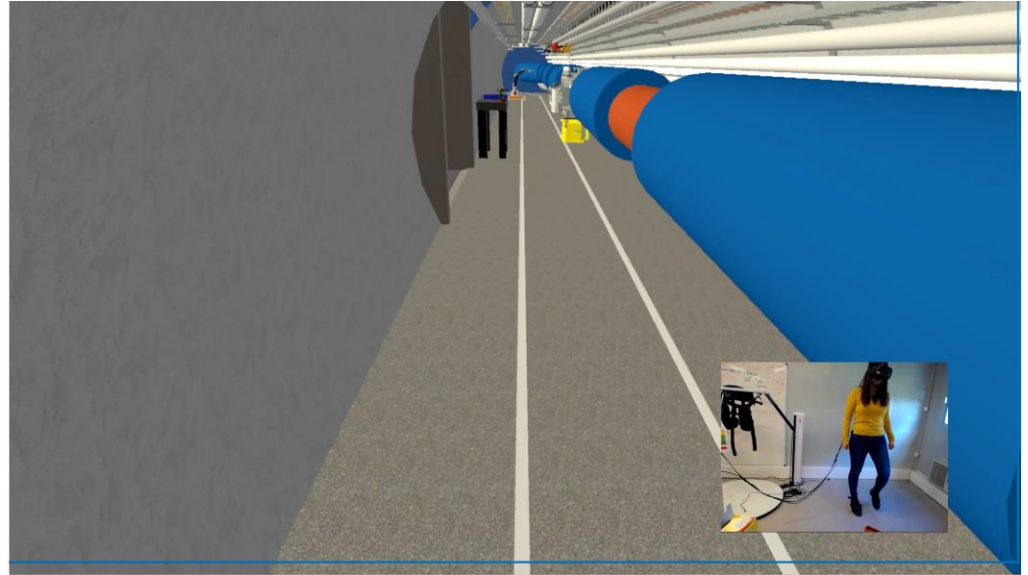
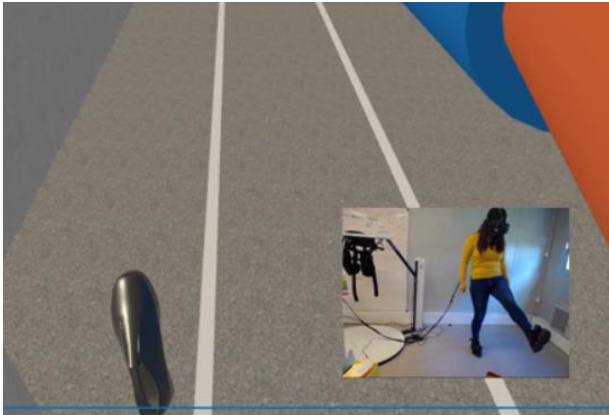


VERO framework

Virtual Environment for intelligent Robotic Operations

Walking module via step tracking

Improving the realism

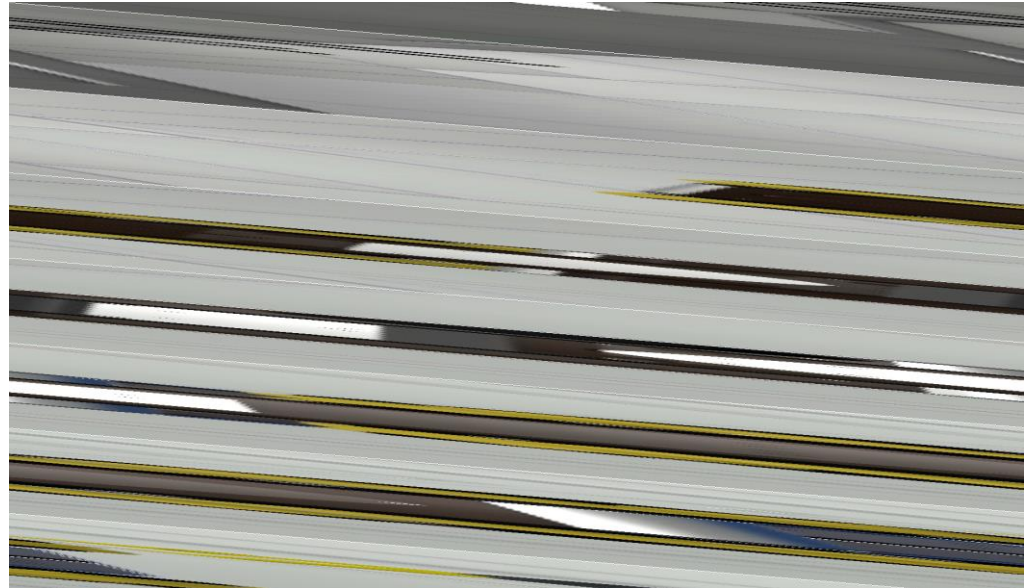
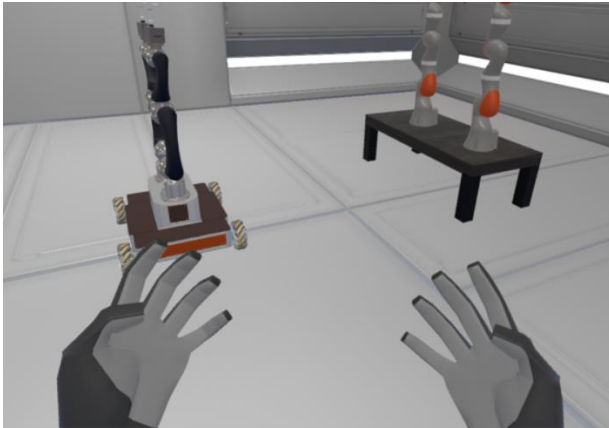


VERO framework

Virtual Environment for intelligent Robotic Operations

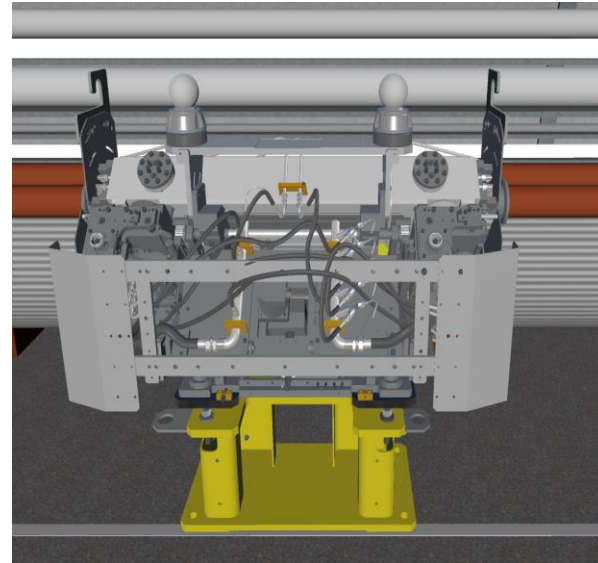
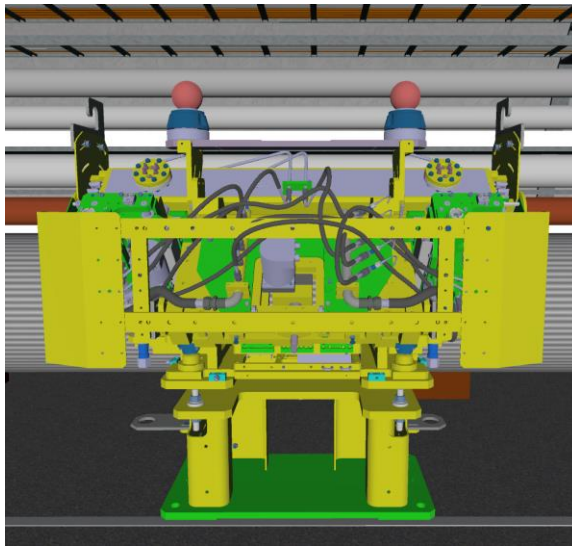
Hand tracking module

Improving the realism



Texture in VR

- Very important to guarantee transparency
- We can import in VR textures of objects from 2D pictures
- Experience in operation with VR and publication has shown that without real texture the gaming effect will be too strong!



Collimator before and after texturing

Texturing in VR

- Strong increase of realism
 - ✓ Helps to go out from the “gaming” effect
 - ✓ Decrease the fatigue and stress while using VR



Augmented Reality for Live Monitoring and Intervention Team Support



- Environmental measurements comes into augmented reality showed on tablet or glasses for example



- Principle adaptable to any robot

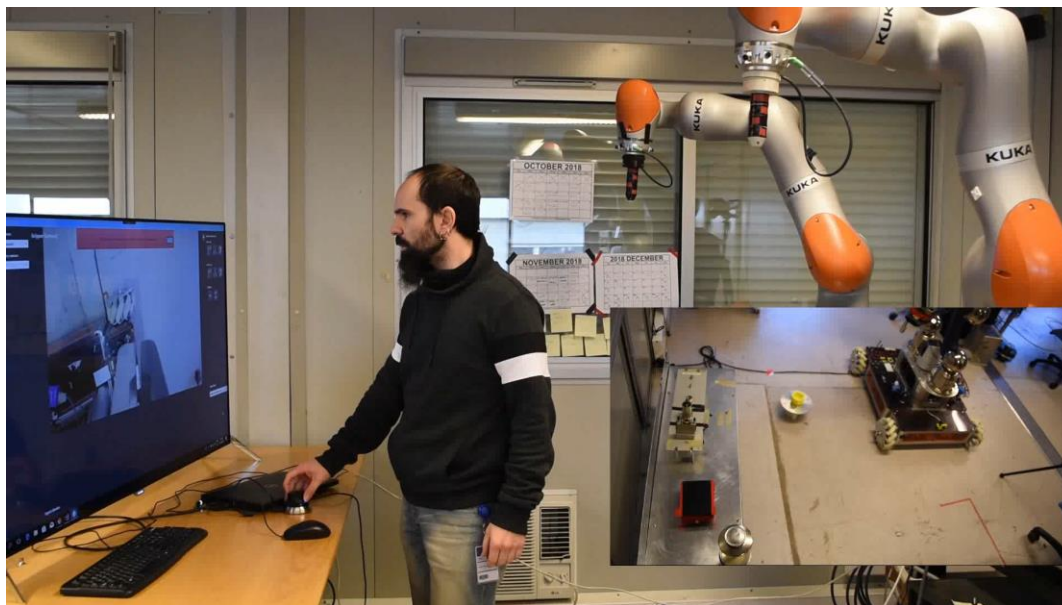
Master-Slave Haptic-Based Teleoperations

- Industrial robotic systems in most of the cases come with a complex master device to operate the robot
 - ✓ **Needs of costly framework to have trained operators**



Master-Slave Haptic-Based Teleoperations

- In house **user friendly** and portable telemanipulation system to allow equipment owners and/or expert technicians to use robot in a “transparent way”
 - ✓ **No need of expert robotic operators**



Why we need haptics?



Unknown and unstructured environment:
How much does it weigh?
What happens if I touch it?
Does it break easily?

Haptics lets you understand your effect on the environment

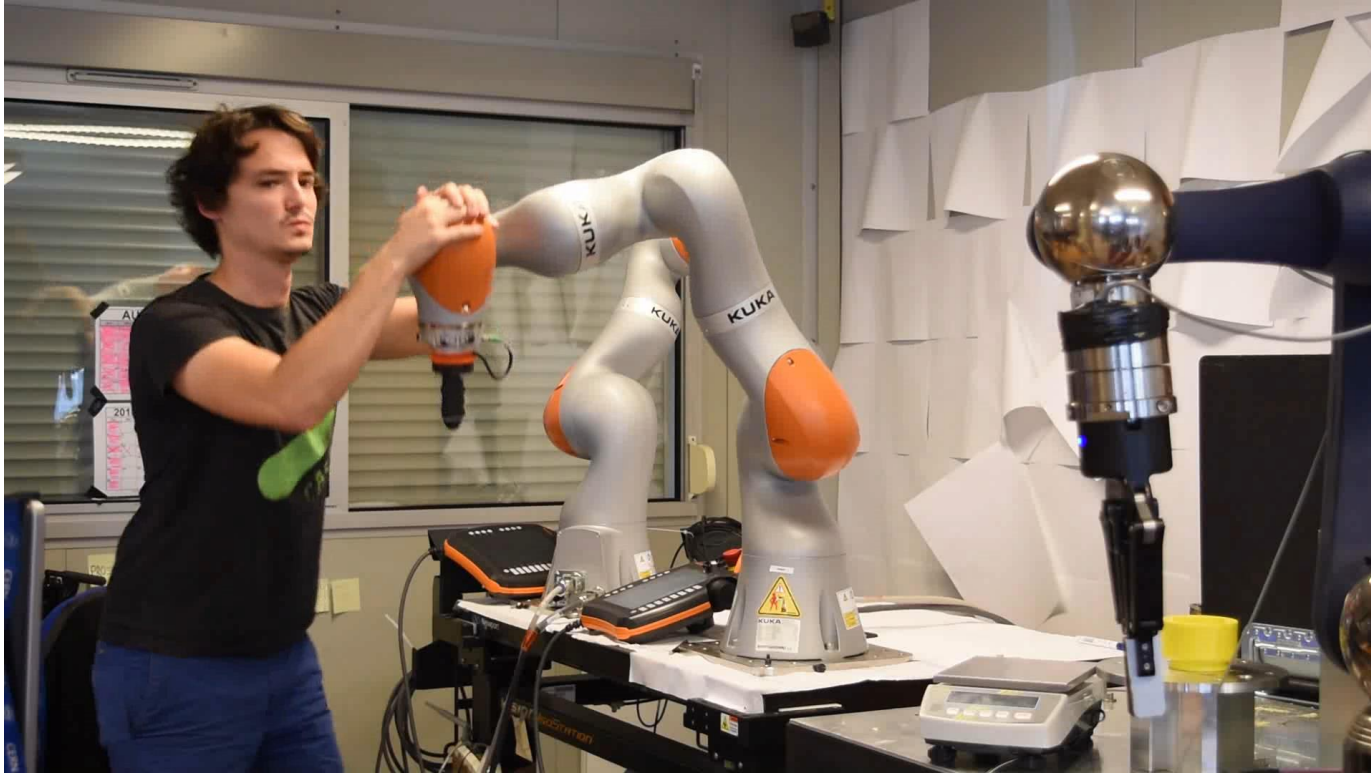
How strong is the robot arm?
How fast can it move?
How much impulse does it have?
Haptics lets you understand the way the robot moves

Stay gentle

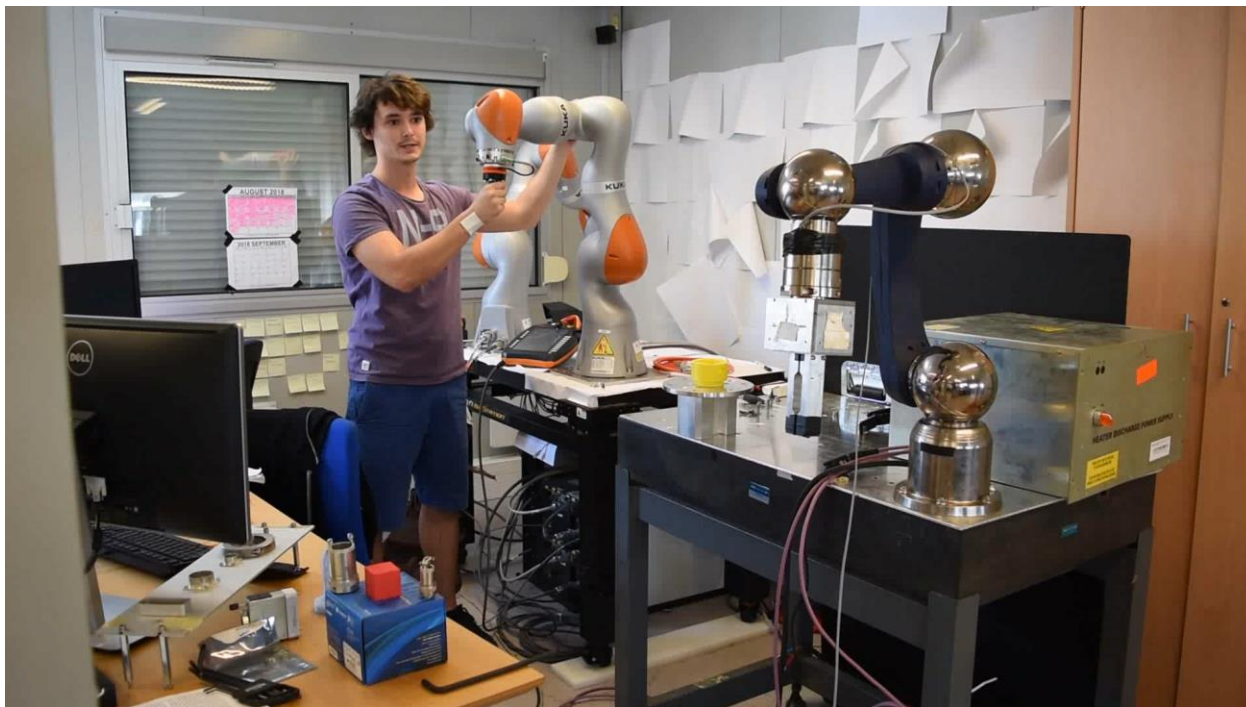


Be strong

Impedance-Mode Control



Master-Slave Haptic-Based Teleoperations



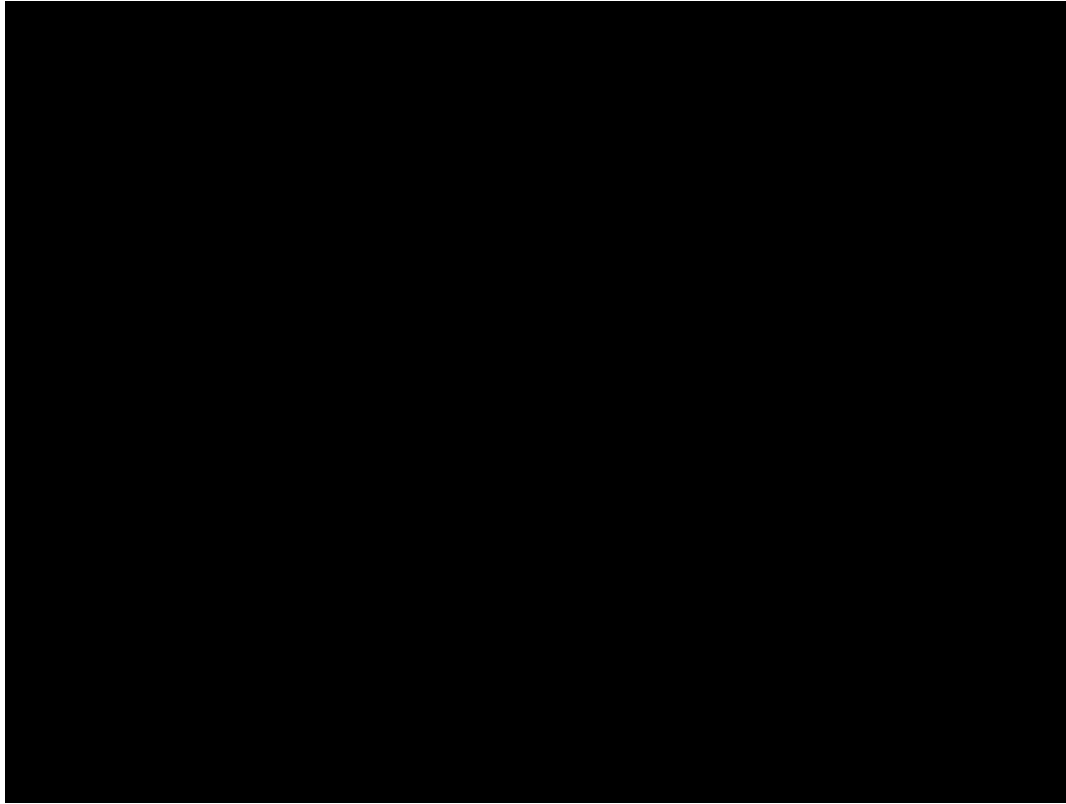
*more on this topic in [7] [26]

User-friendly telemanipulation and advanced controls

Adaptive force feedback

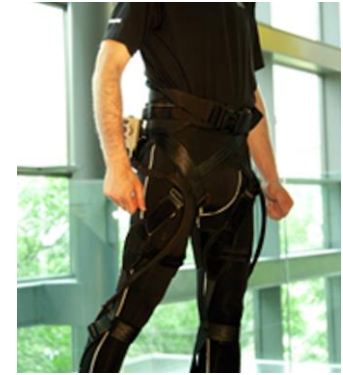


Depth estimation using monocular cameras



R&D for Exoskeletons

“Exoskeletons are wearable devices that work in tandem with the user. Exoskeletons are worn on the user’s body and act as amplifiers that augment, reinforce or restore human movements”



R&D for Exoskeletons

Objectives of the Project (ExoFlex - DPI2015-68842-R)

- Developing a soft exoskeleton (exosuit) to assist the upper limbs
 - ✓ Elbow
 - ✓ Shoulder
- Reduce the metabolic rate of the user
- Lightweight
- Cable-driven



POLITÉCNICA

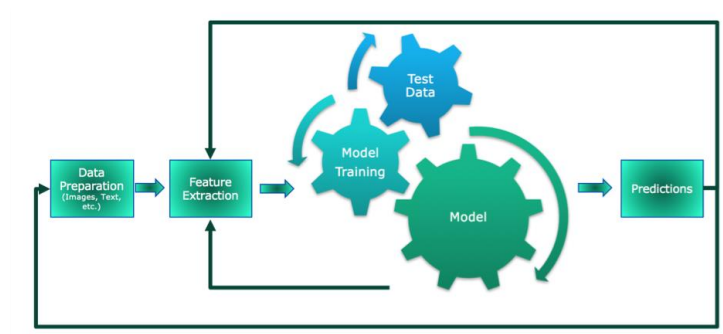
CSIC
CONSEJO SUPERIOR DE INVESTIGACIONES CIENTÍFICAS

Contents

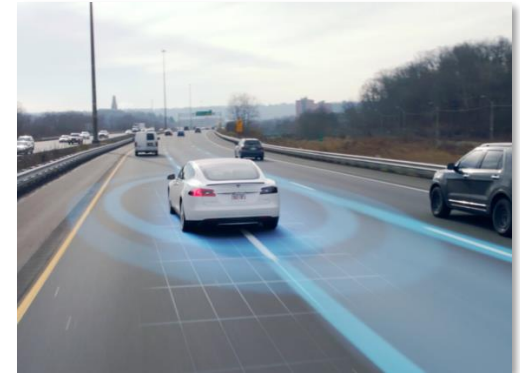
- Introduction to Robotics
- Needs and Challenges for Robotic Solutions
- Operational Systems
- R&D and **Artificial Intelligence**
- Conclusions

Machine learning

- Allows software to learn from training data in order to learn statistical models of real world problems
- Machine learning is not a new technology (first prototypes of statistical learning from early 1970s)
- Latest advances in computing power and hardware development allow practical execution of machine learning algorithms
- Enormous effort in software and hardware development in place by biggest companies (e.g. Intel, Google, Apple, Nvidia) makes the research field extremely dynamic
- Wide variety of Open Source library for fast prototyping and development



A machine learning typical pipeline [38]



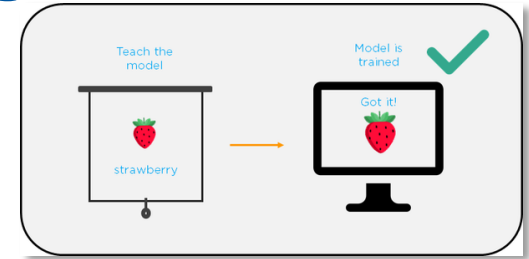
Application of machine learning to real life scenarios



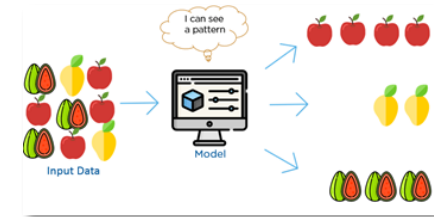
Machine learning categories

➤ Three main categories [38]:

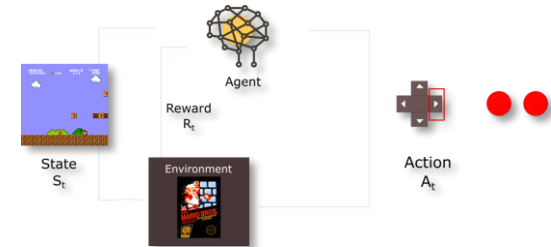
- ✓ Supervised
- ✓ Unsupervised
- ✓ Reinforcement



Supervised learning



Unsupervised learning



Reinforcement learning

➤ *Supervised learning* learns from a prepared set of labeled data

- ✓ The algorithm will be able to observe a new, never-before-seen value and predict its label

➤ *Unsupervised learning* learns from random data using tools to understand the properties of this data

- ✓ The algorithm will be able to group, cluster, organize data

➤ *Reinforcement learning* learns from its own mistakes

- ✓ It uses a “satisfaction” function to distinguish between a good and a bad behavior
- ✓ The algorithm will be able to choose and perform actions

Machine learning in robotics #1

- 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 [39]



Saliency detection (center of attention) in self-driving cars for situational awareness [40]



Human Robot collaboration for mechanical assembly

Machine learning in robotics #2

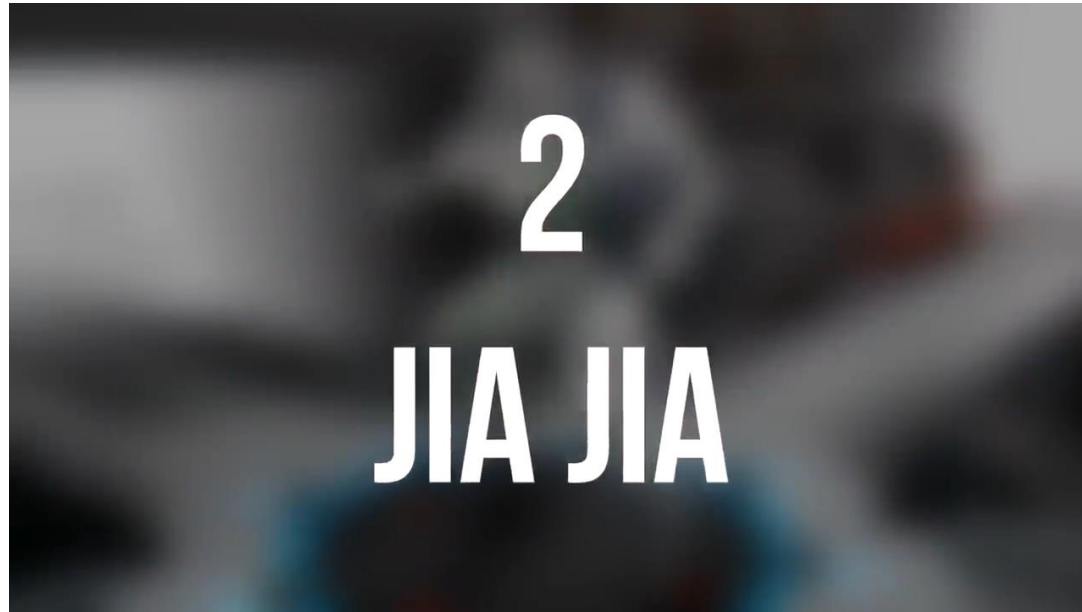
- **Robot still do not appear fast enough**
 - Slow in decision making
 - Difficult to adapt to real world scenarios



Robot still don't appear fast enough [41]

Machine learning in Robotics #3

- Robotics community is investing strongly in machine learning adapted to social robotics



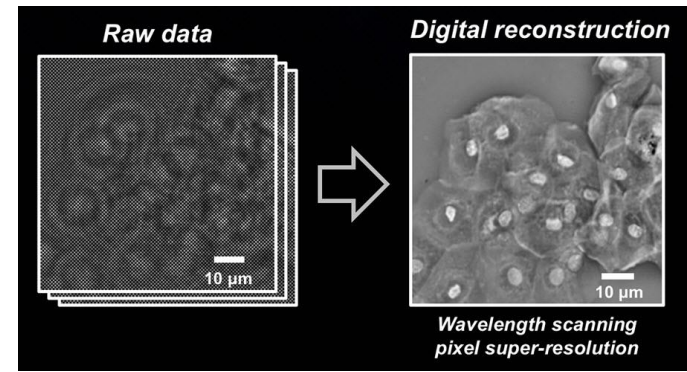
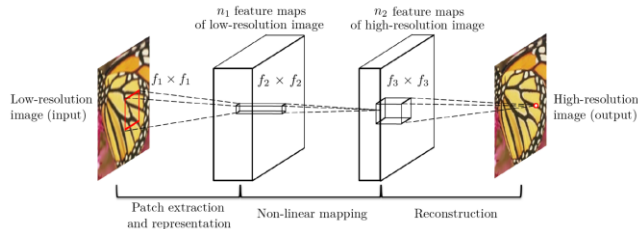
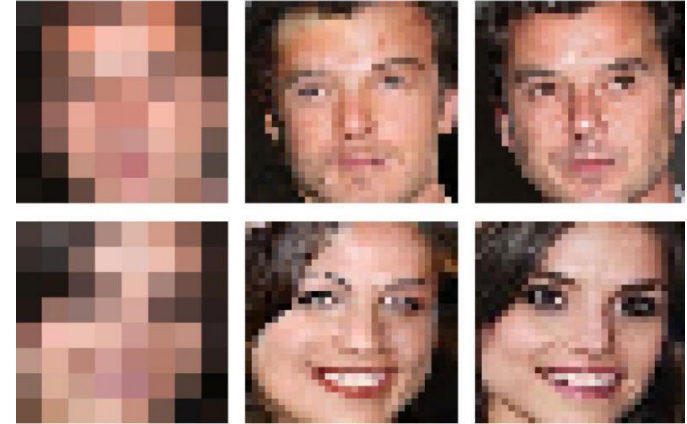
Object detection and recognition for Teleoperation #2

- Machine learning (Faster-RCNN) is used to assist online grasping tasks in teleoperation
 - ✓ Visual servo control endorsed with AI [57]
- Object detection embedded in CERN Human-Robot Interface to process live images endorsed with super resolution techniques [44]



Super resolution for visual online monitoring #1

- Generates higher resolution less noisy images from small resolution compressed images
- Two categories:
 - Single image super-resolution [45]
 - Multiple image super-resolution [56]
- State-of-the-art neural networks produce great results but are not suitable for real-time display



Super resolution for visual online monitoring #2

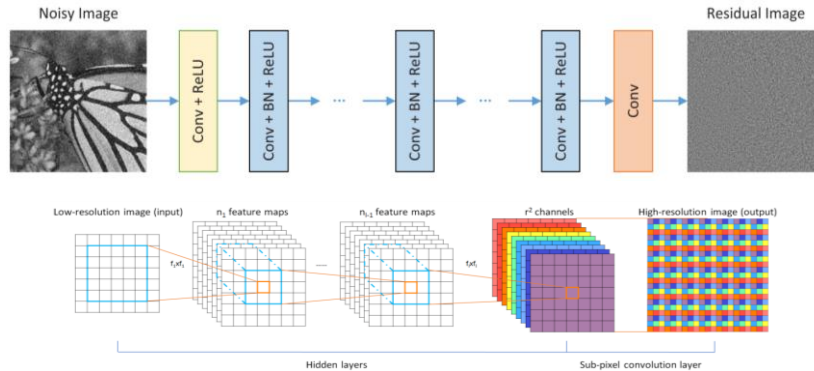
- We merged 2 neural networks : compression noise reduction and resolution enhancement [47]
- Reduce 4G bandwidth consumption for transmitting images
- Generates no lag thanks to real-time capabilities
- Little defects in some images are not critical as images are displayed to the operator at 15 fps
- Multiscale super resolution available (2x, 4x, 8x etc.)



50% jpeg compression; 14 kb



4X resolution enhancement + noise reduction; 282 kb; computation time 4 ms



Learning by Demonstration

- **Robots can learn complex tasks**
- **Learning Benefits**
 - ✓ Robot fast adaptation to new tasks and the environment
 - ✓ Fully autonomous task implementation



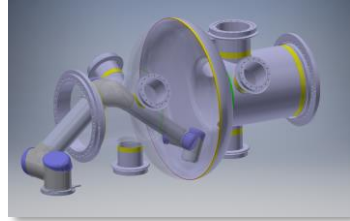
Learning by demonstration: fusing Fast-RCNN [48] and DMP for dynamic environment



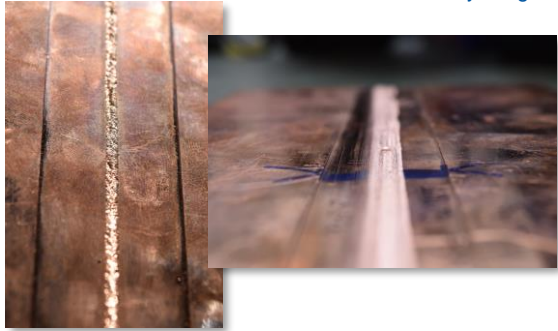
HL-LHC RF cavities: proof of concept for internal welding polishing using a robotic arm (learning by demonstration techniques)



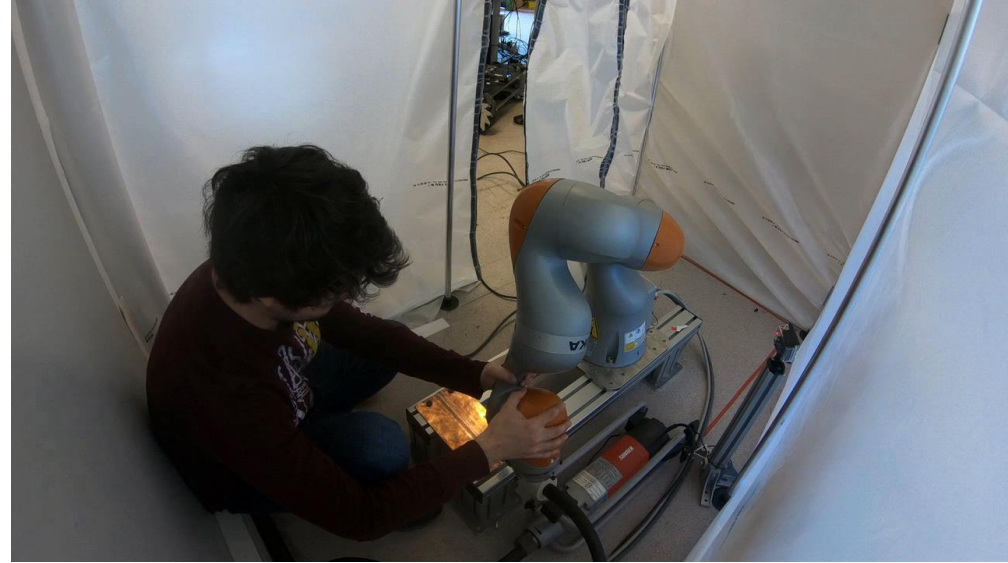
Picture of a cavity



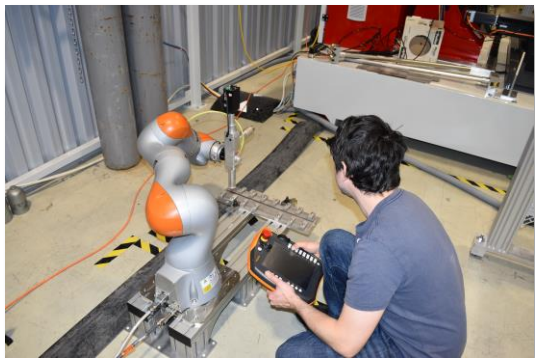
Preliminary integration



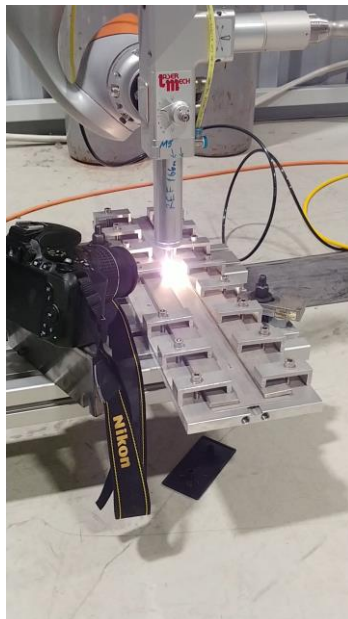
Preliminary results of a polish on a welded joint.
Before polishing (left) and after polishing (right)



Proof of concept for laser welding for HL-LHC triplets beam screen using a robotic arm (learning by demonstration techniques)



Learning by demonstration



Execution of the welding



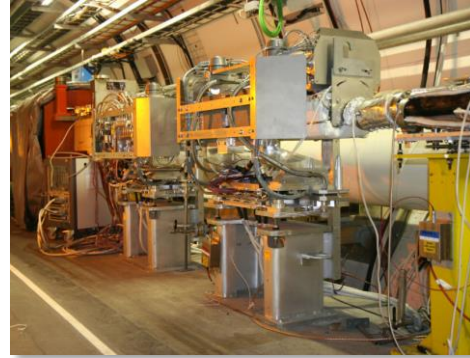
Very promising preliminary results

TIM Survey Wagon alignment to fiducials (Fast-RCNN)

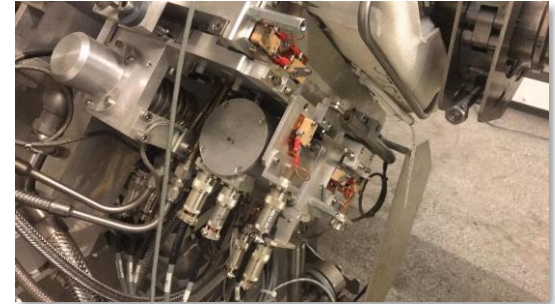


Autonomous tests of LHC Collimators switches (Fast R-CNN + learning by demonstration)

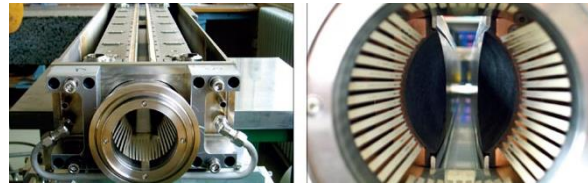
- Deep learning for object and pose recognition
- Machine learning for autonomous operations
- Safety using virtual fixtures to avoid collisions



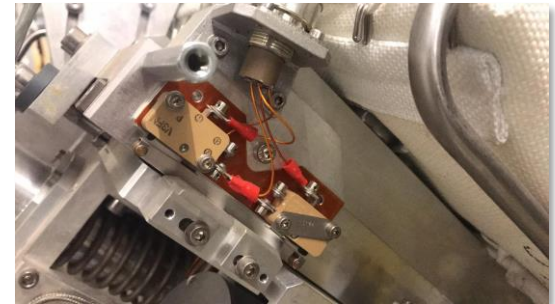
LHC Collimators



LHC Collimators position switches plate



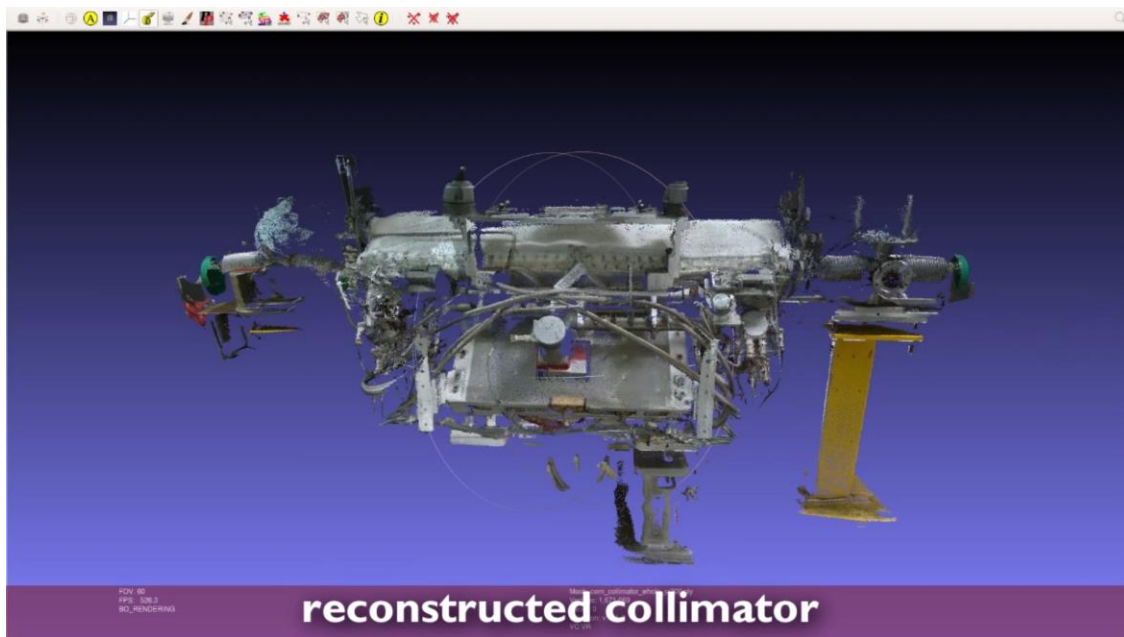
Internal view of the LHC Collimators



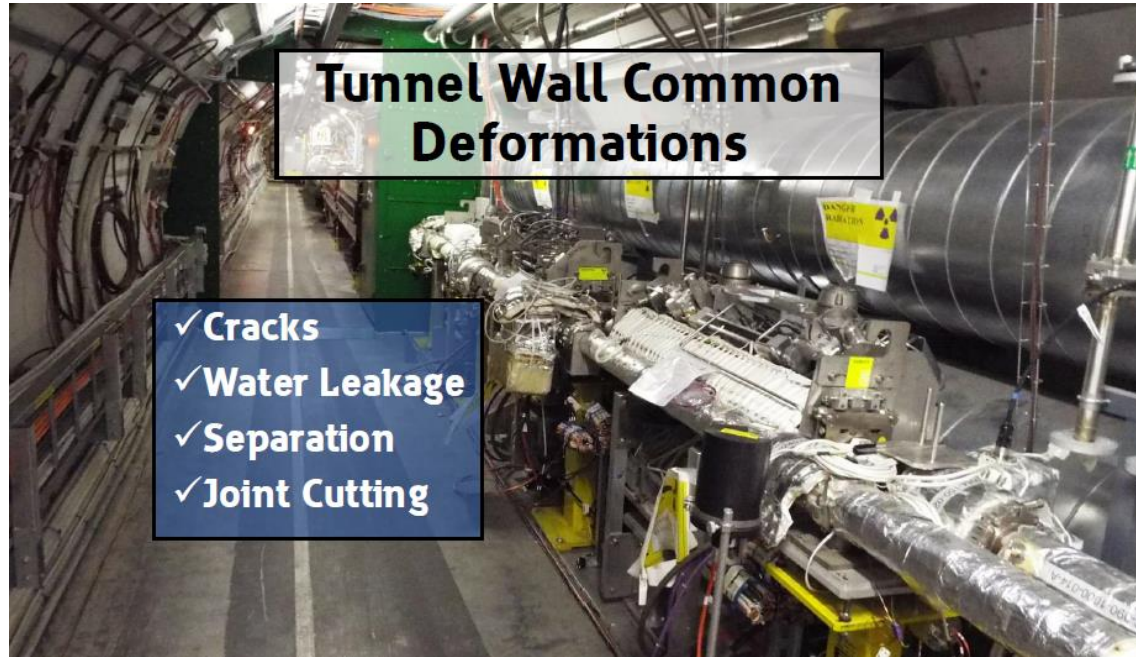
Close view of the LHC Collimators position switches

Autonomous tests of LHC Collimators switches (Fast R-CNN + learning by demonstration)

- Deep learning for object and pose recognition
- Machine learning for autonomous operations
- Safety using virtual fixtures to avoid collisions

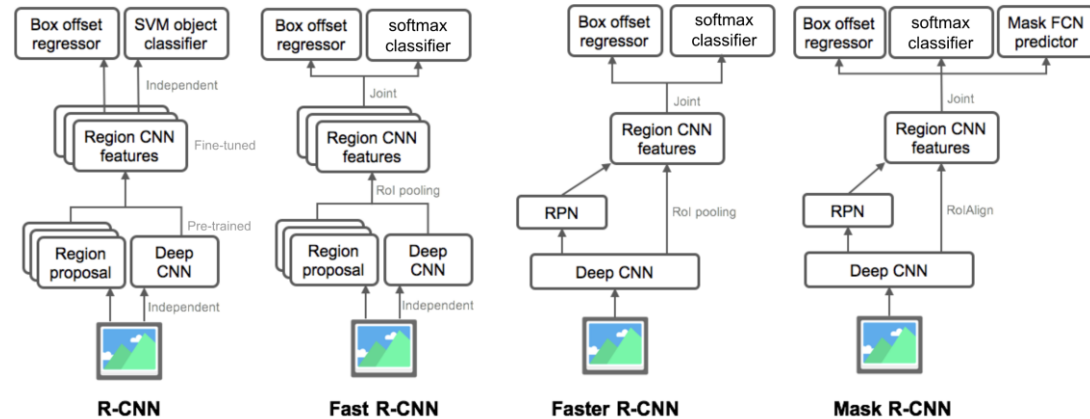


Digital Image Processing and Photogrammetry for Tunnel Structure monitoring



Tunnel structure monitoring with defects detection

- Faster-RCNN provides simple bounding boxes around the recognized object
- Complex applications require more detailed detection
- Mask-RCNN [51] provide accurate segmentation around the recognized object



Examples of object recognition using machine learning

Online Tunnel Structure Monitoring

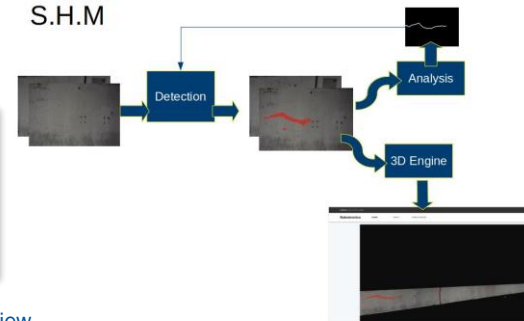
- Detects defects (cracks, water leaks, changes [51-52]) using a Mask-RCNN network.
- High-definition picture collection using TIM and CERNBot
- 3D reconstruction of wall using Structure from Motion techniques to compare time evolution of defects (available on web browser or virtual reality headset)
- Complete application under commissioning, from data collection to data analysis



HD cameras mounted on TIM and CERNbot



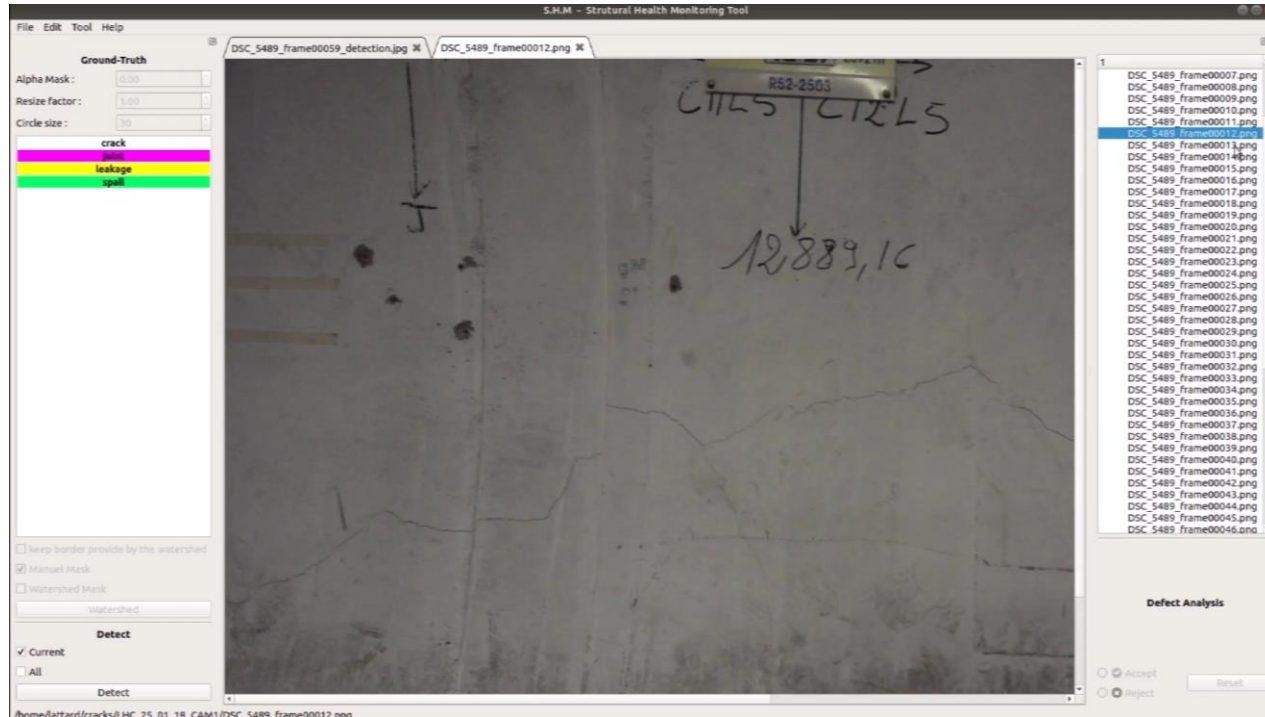
HD camera system for tunnel dome view



Scheme of the working principle

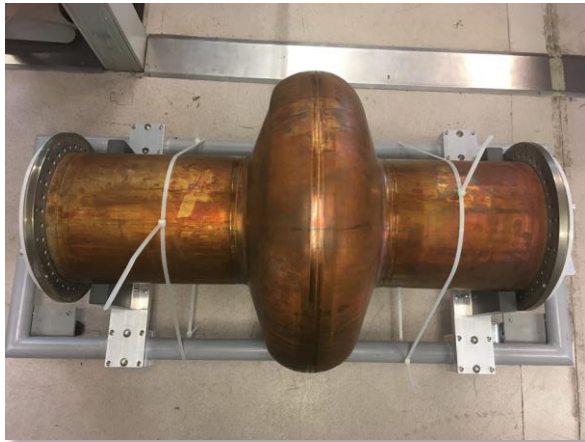
Tunnel Structure Monitoring

- Continuous training by live correction improves results as the dataset grows

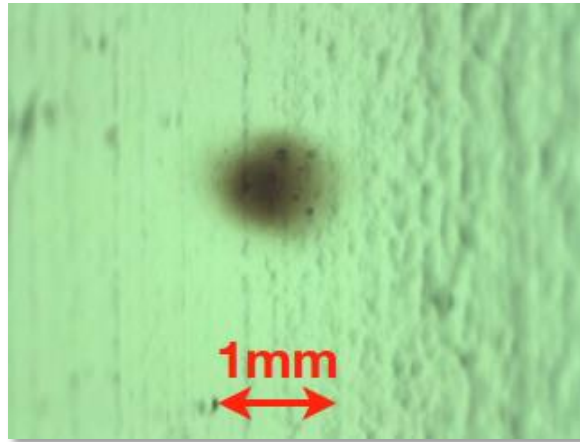


Visual based RF cavities quality control

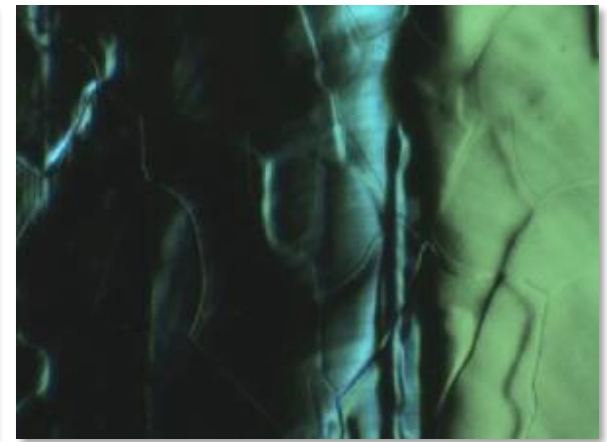
- Same technique used for defect detection is applied to surface quality control of the HL-LHC RF cavities



HL-LHC RF cavity



Anomaly (burn)

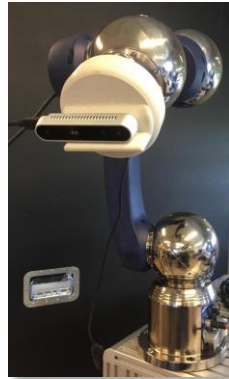


Welding cracks

Courtesy of A. Macpherson

Object Detection and Pose Estimation for Measurements and Calibrations Sensors Approach

- Faster-RCNN network for online 2D Beam Loss Monitors (BLM) localization [49]
- Multiple RGB-D cameras used for 3D reconstruction of the environment
- Bounding boxes generated by Faster-RCNN on each camera allow triangulation of the bounding box in the space
- ICP algorithm [50] on the depth sensor allows accurate 3D localization
- 3D pose will be used by the robotic arm path planner to calculate a safe approach to the BLM in the reconstructed environment



INTEL 3D camera on robot arm end effector



BLM recognition

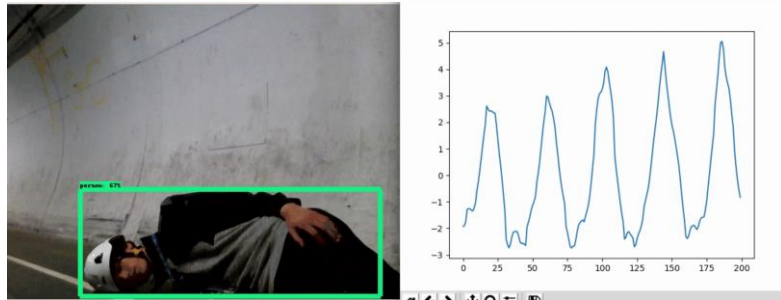


People recognition and vital monitoring

- 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



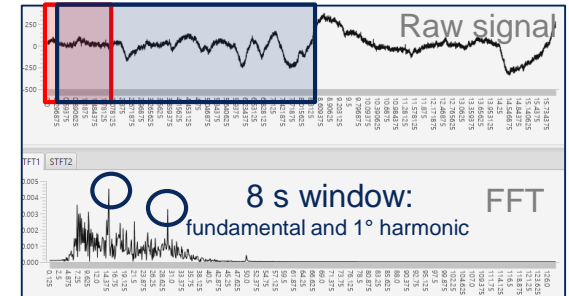
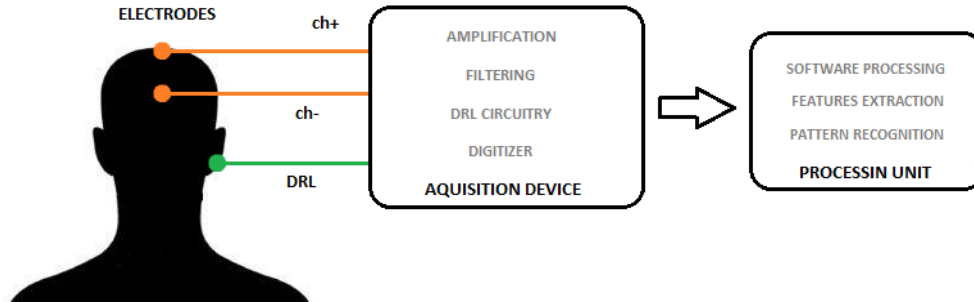
Online people recognition and tracking

Brain-Robot Interface for robot arm control

- Online analysis of brain signal
- Augmented reality glasses used for commands display
- Eyes focus point detected by CNN processing Steady State Visual Evoked Potentials (SSVEP) which are synchronous responses produced in the visual cortex area when observing flickering stimuli

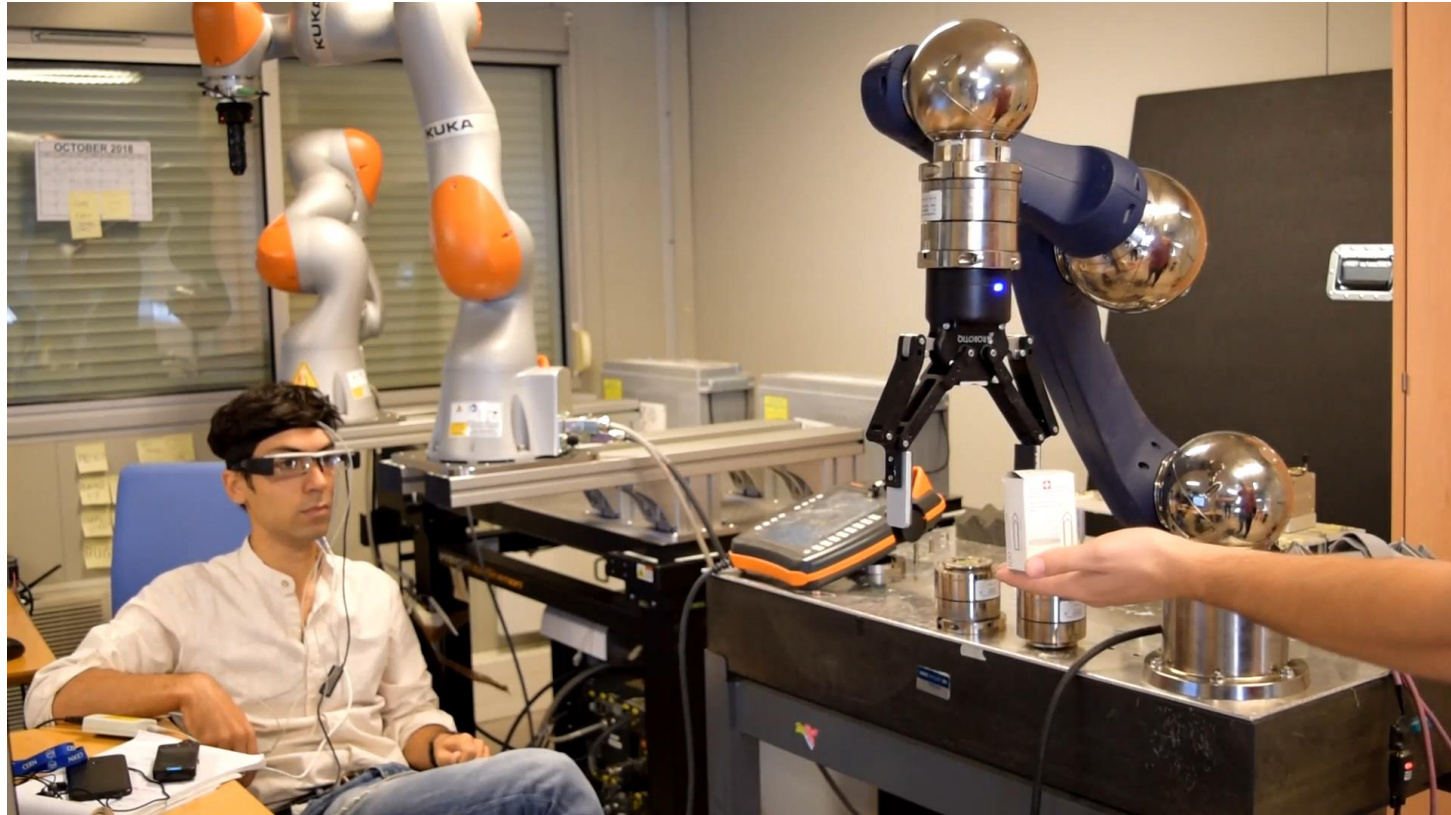


Hardware used for the brain monitoring



Example of brain activity monitoring

Brain-Robot Interface for robot arm control



Impact

Industry

- Problems to solve (a “solution deficit”)
- Technology and experience
- A need for qualified staff
- Limited budgets

Universities

- A “problem deficit”
- Research expertise
- Training skills
- Well-qualified students looking for jobs

Impact

- **Robots for search and rescue**
 - ✓ Knowing the environment before the fire brigade intervention
 - ✓ Find possible entrance in catastrophic zone
- **Inspection of buildings, pipes etc.**
- **Logistics**
- **Staff localization in harsh environment**
- **Nuclear plants decommissioning**
- ...



Knowledge Transfer

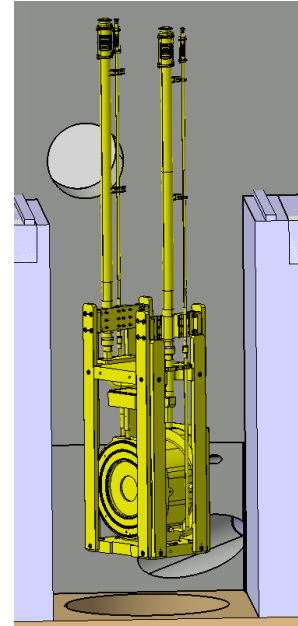
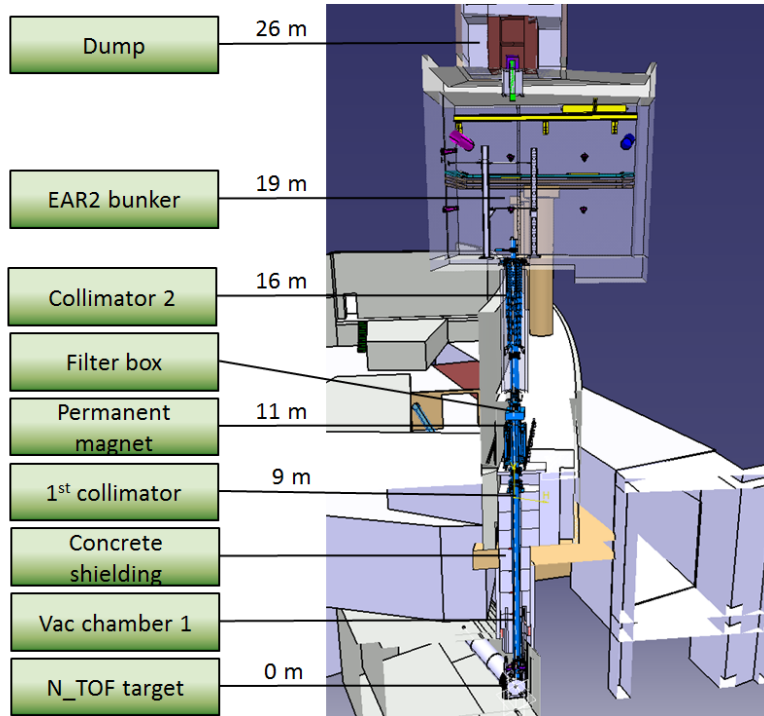
➤ Knowledge transfer with Ross Robotics

- ✓ KT on robotic controls, autonomous navigation, perception and teleoperation



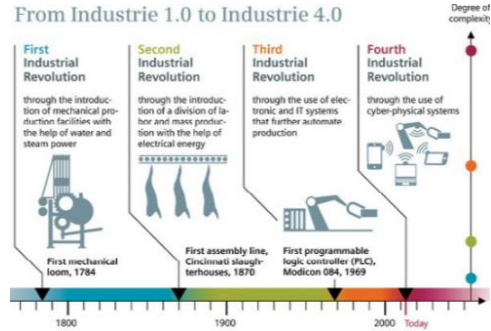
Main Challenge for 2019

N_TOF EAR2 beam line

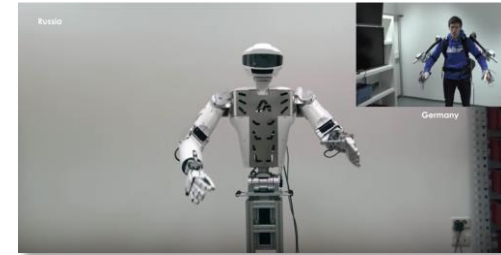
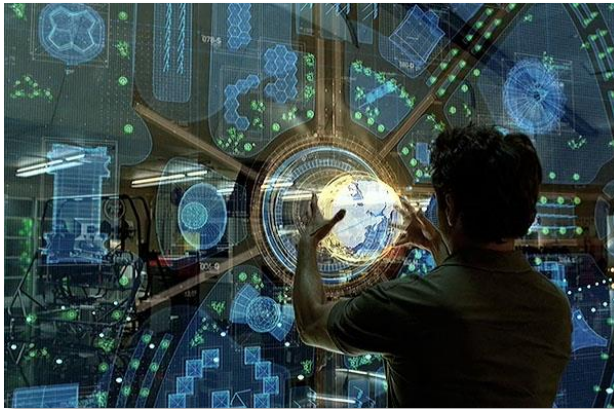


+ More than 20 robotic interventions planned

Future technologies?

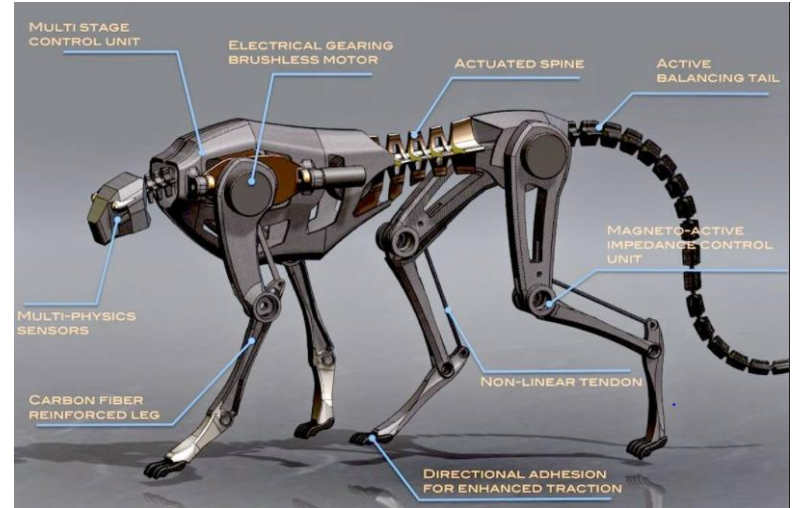


Industry 5.0?



Future robot?

Inspired by nature



Bachelor, Master and PhD students



UNIVERSITÀ DEGLI STUDI DI NAPOLI
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Lesson Learnt an Conclusions

- **Designing machines that can be maintained remotely using appropriate and easily accessible interfaces will drastically increase the availability and decrease human exposure to hazards**
- Intervention procedures and tools are important as the robot/device that does the remote intervention
- R&D and continuous developments models are needed because ready-to-use robotic solutions that can fulfill CERN needs for remote inspection and user-friendly teleoperation do not exist
- EN-SMM has acquired knowledge and expertise to provide robotic support and robotic-friendly design guidelines to other CERN groups according to the resources available
- External strategic collaborations with research centres and universities are crucial to take advantage of the cutting edge technology and to find the right people for CERN



Robots and robotic instrumentation need a crew to use them and maintain and experts in-house to be effective

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Thank you for your attention

