UK Atomic Energy Authority

UKAEA-RACE-PR(22)04

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This is a preprint of a paper submitted for publication in Robotics

Article

Robot Assisted Glovebox Teleoperation for Nuclear Industry

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Abstract: The nuclear industry has some of the most extreme environments in the world, with radiation levels and extremely harsh conditions restraining human access to many facilities. One method for enabling minimal human exposure to hazards under these conditions is through the use of gloveboxes which are sealed volumes with controlled access for performing handling. While gloveboxes allow operators to perform complex handling tasks, they put operators at considerable risk from breaking the confinement and, historically, serious examples including punctured gloves leading to lifetime doses have occurred. To date, robotic systems have had relatively little impact on the industry, even though it is clear that they offer major opportunities for improving productivity and significantly reducing risks to human health. This work presents the challenges of robotic and AI solutions for nuclear gloveboxes, and introduces an integrated demonstrator proposed for robotic handling in nuclear gloveboxes for nuclear material handling. The proposed approach spans from tele-manipulation to shared autonomy, computer vision solutions for robotic manipulation to machine learning solution for condition monitoring.

Keywords: nuclear robotics; tele-operation; machine learning; glovebox

Citation: Tokatli, O.; Das, P.; Nath, R.; Pangione, L.; Altobelli, A.; Burroughes, G.; Skilton, R. Robot Assisted Glove Box Teleoperation for Nuclear Industry. *Robotics* **2021**, *1*, 0. https://doi.org/

Received:
Accepted:
Published:

1. Introduction

Robots are indispensable tools for manipulation in challenging environments such as nuclear applications. Robotics in the nuclear industry can not only ensure the safety of the operators from the unsafe levels of radiation; but also provide cost-effective solutions for manipulation, inspection and maintenance of nuclear sites.

The extreme conditions encountered in the nuclear industry leads to a conservative attitude towards cutting-edge robotics technology which has a high potential for solving the problems that the industry faces. In order to bridge the gap between state-of-the-art robotics research and the nuclear industry, the Robotics and AI in Nuclear (RAIN) Hub was/has been established where various problems encountered on nuclear sites are investigated and solutions are being developed.

One of the problems considered in the RAIN Hub is introducing the modern robotics and AI technology into the existing gloveboxes and paving the path for the next-generation glovebox designs. Our approach covers a wide range of technologies from computer vision to teleoperated robotics, assistive technologies to machine learning and we are aiming for safer and efficient operations with nuclear gloveboxes.

Nuclear gloveboxes are contained environments for safe handling of hazardous objects and materials. As for all nuclear applications, the safety of the operator using the glovebox is the primary goal for every operation inside the glovebox. To establish safe operational conditions, operators are equipped with personal protective equipment (PPE) and required to closely follow operational rules. However, glovebox operations do not fully mitigate all hazards, and remain high risk activities for the operators [1].

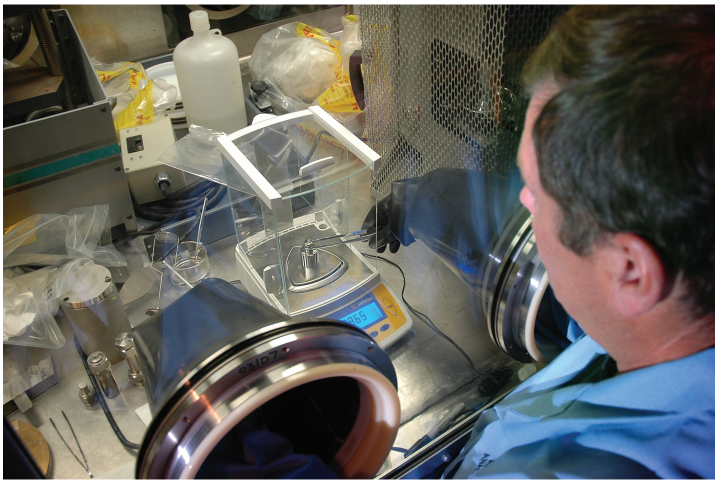

Figure 1. A nuclear glovebox where the access to the interior is through the glove ports. The operator is wearing the specially designed gloves to protect himself from the contamination. Source: Wikimedia Commons

Using PPE and working in a confined space with additional safety procedures lowers the manipulation capabilities of the operators. Gloves severely reduces the tactile feedback from the hands. Moreover, working through glove ports which limits the arm movements of the operator introduces further challenges during handling high risk objects inside the glovebox. As a result, a simple task of opening a screw lid of a container becomes a strenuous and challenging task for the operator.

Gloveboxes, such as in Figure 1, may be cluttered, dynamic environments, and the tasks executed within can be complex, numerous, safety-critical, and often one-of-a-kind; therefore, a stand-alone autonomous robotic system cannot be expected to out-perform a human operator with the current technology. Moreover, due to safety concerns, human-in-the-loop solutions are deemed to be more desirable at least in early phases of deployment.

Novel technologies in robotics and artificial intelligence can be exploited to increase the safety in the legacy glovebox or to design new robotic gloveboxes; in both cases, dexterous robotic manipulators, sensors and control algorithms can avoid the direct contact between the operator and hazardous material. Inside the unstructured environment of gloveboxes, the robots could be controlled by the operator via teleoperation while more autonomous control strategies could be exploited in more standard tasks. Robot arms could be profitably used to accomplish operations that are performed by the operator in order to reduce the workload and the risks of accident or contamination.

The following presents the problem of nuclear glovebox robotics, and an integrated demonstrator into a proposed robotic handling system for Nuclear Gloveboxes, spanning teleoperation to autonomy. The paper is organised as follows. In Section 2.1 nuclear gloveboxes are introduces and the challenges for robotics and AI is presented. Section 3 presents the previous work on the use of robotics technology in nuclear gloveboxes. In Section 4, the hardware and the simulator build based on this hardware is presented. Section 5 defines the individual research areas and describes how they address the challenges. Finally, Section 6 concludes the paper.

2. Challenge Statement

2.1. Glovebox Challenges

The majority of robotic application that achieve success enjoy structured, known, open environments where obstructions to motion and sensing is minimal. Morevoer, the operational conditions are expected to be *clean* and *suitable* to the mechatronic systems as to not cause damage to the mechanisms and electronics. On the contrary, the working conditions inside the nuclear gloveboxes are considered to be dirty, dark, dull, dangerous

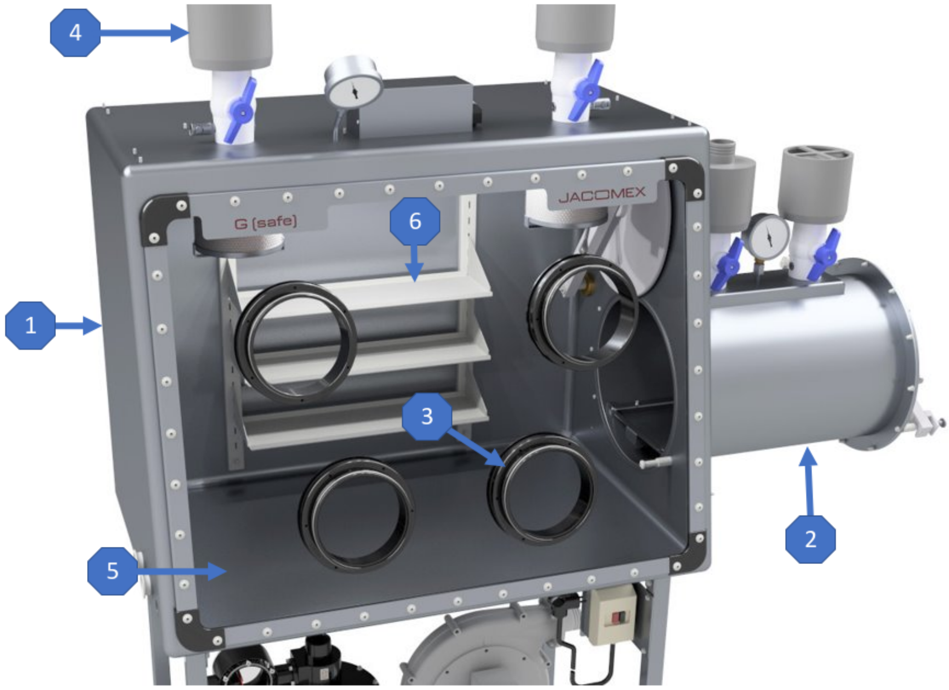

Figure 2. Glovebox illustration. (1) Hull, (2) Posting in/out port, (3) Glove ports, (4) environmental monitoring/maintenance equipment, (5) glovebox window, and (6) Glovebox internals.

and cluttered. Therefore, a thorough understanding of gloveboxes is the key for the success of the robotic solution.

Gloveboxes are broken into 6 major components, which is illustrated in Figure 2: hull, windows, glove ports, posting ports, monitoring equipment and the glovebox internal.

2.1.1. Hull

The hull is the primary component of the glovebox which separates the glovebox internal from the external environment. In some glovebox solutions, the encloses a vacuum or a pressurised inert gas to ensure containment of the radiation hazard. The hull is often lead lined for improved shielding. Due to the hazards inside the glovebox, it is imperative that the hull is not damaged or containment breached.

2.1.2. Windows

The windows allow for operators to see within the glovebox. The glass is often doped with lead to increase its nuclear shielding; however, over time it is common for this glass to become yellowed (with lower visibility) and brittle from radiation damage. It is not uncommon for the glass to become crazed, further weakening integrity of the containment, and reducing visibility.

2.1.3. Glove Ports

These are fixed holes in the hull that allow for the gloves, and hence the operators, to penetrate the hull. They are normally of a standard fixed dimension (eg. 11 cm in radius), and most gloveboxes have multiple ports dotted around the hull to enable operators to reach anywhere in the glovebox interior. These ports have a fixed method for replacing them without losing containment and can house ports for non-gloves, such as cable routing. The gloves used by the operators are often thick, heavy, leaded, and when under pressure require the operator to hook their hands into them with their last 2 fingers to stop their hands being forced out. Overall, the glove design significantly increases the operator safety while sacrificing the dexterity and reducing the manipulation capability of the operator.

2.1.4. Posting in/out ports

These ports allow operators to post items in or out of the hull through an airlock, which maintains the containment. Before posting out the items, they must be ensured that they are appropriately decontaminated. The posted out items are double bagged, and they are of a limited fixed size.

2.1.5. Environment monitoring and maintenance equipment

These are the equipment for monitoring the glovebox internal, maintain any containment requirements (e.g. vacuum, temperature), and, also, performing containment testing (e.g. leak tests).

2.1.6. Glovebox internals

The glovebox internals include the operational equipment used by the operators, this is a wide and diverse set of objects, from chemical processing equipment to powered hand tools (e.g. Dremels). Any operation for handling nuclear material/objects is performed in the glovebox internal.

As an example of a nuclear application consider post-operational clean-out operations (POCO), this requires nuclear gloveboxes that have been in service for decades to be dismantled and decontaminated from the inside-out, surveying, separating waste and radio-logical wastes, reducing size of elements through deconstruction or cutting, draining liquids from process plant equipment, sweeping, and posting contained elements out.

Beyond this it is common for operators to require additional complex PPE, or other equipment such as ladders to be able to access the gloveboxes, whilst exposing them to a reduced amount of contamination.

2.2. Challenges of Robots in Gloveboxes

Whilst reducing the amount of time human arms are required in gloves reduces the risk to operators, new challenges are posed to the robots. POCO shall be used as the primary use case as it covers a wide range of complex tasks in nuclear gloveboxes.

Mechatronics Challenges

First issue robots must enter the area, in a new glovebox they can be built into the internal of the hull, but this causes issues for maintenance of the robot, as they then must be maintained in location. Alternatively, the robot can access the area through the glovebox ports. This then requires the robot to be able to fit through the glovebox port, whilst also having a long reach and a payload capability similar to a human. It is worth noting this pushes the robots towards an inline joint configuration, rather than offset approach such as used by Universal Robots, for example.

Another consideration is whether the robot should be in the glove or affix directly to the port. The environments are filled with dust and detritus, that can damage joints. Moreover, it preferred that robots do not become contaminated to simplify maintenance. This then pushes robot designs to being in the gloves. Manipulating from inside the glove will apply pressure to the robot and limit rotations and dexterity. It is worth noting that the end-effectors may be on the inside of environment, connected to the robot through a modified glove that can dock a robot and end-effector.

In a similar fashion, the glove may have a window modified into it to allow the robot to have a wrist camera. External sensors may be challenging to install as their cabling, and themselves will have to be posted in, or they have to be able to cope with the reduced visibility glass interfering with their functioning. In the case of posting in, that will require the sensor to have be able withstand the environment, a mechanism for power and data to be connected without breaking containment, and affixing method to be determined. Moreover, it increases secondary waste generated in the decommissioning process. Secondary waste, is waste generated in the process of decommissioning primary waste.

Other things to note, that while robots that replicate human physiology will have an advantage in being able to replicate operations. But other robot kinematics will have their advantages, such as slender continuum robots, which will have advantages in inspecting complex shapes and internals such as pipes.

Another significant challenge is radiation, which will degrade many parts of the robot.Gamma radiation is the most challenging type of radiation to protect a robotic system from in nuclear gloveboxes, due to its penetrating power. Standard robotic components and materials such as semiconductors (used in sensors, local motor drive electronics, etc.), plastics, optical components and lubricants are degraded or rendered unusable after certain levels of accumulated Total Integrated Dose (TID) of Gamma radiation.

Because the damage is done over time as a consequence of the accumulating dose, limiting the amount of time the robot is in the glovebox to active operations is a good first step to extending its useful lifetime, but this then requires a reliable method for insertion and removal which reduces human intervention.

There are different approaches for dealing with this issue. One method is to utilise standard COTS components which are replaced on a regular basis and/or as they stop functioning. This has the advantage of being achievable with commercially available technologies but puts requirements on the glovebox/robot design such that all "perishable" components are easy to remove and replace and that a robust safety system is in place to handle any unexpected robot failures at inconvenient times - the time to failure due to radiation cannot be easily predicted in COTS devices which have not been designed with this environment in mind. There is also the risk of creating further secondary waste from this process.

A better long-term approach to this challenge is to use radiation hardened components which are designed, manufactured and certified to withstand a particular TID before failing. Historically, such technology has mainly been developed for use in the space sector, but electronics designed for spaceflight are often prohibitively expensive, and the space environment is more concerned with protecting devices from the effects of charged particles and high-energy electrons than gamma radiation [citation?]. Traditionally, the nuclear sector has been able to work around the lack of radiation-sensitive equipment through the extensive use of shielding and simple electro-mechanical solutions, but the maturing field of Nuclear Fusion has created a strong research push towards radiation tolerant sensors and electronics. For example, devices such as Digital Camera image sensors , AD/DC converters and X drives are now in advanced prototype and/or early commercialisation stages.

2.2.1. Control and Intelligent Systems Challenges

Now that there is a robot reaching into the environment, the next set of challenges present themselves. The biggest element of this is that these robots should be aiming to match or outperform the human operator.

Robotic solutions for gloveboxes mostly rely on teleoperation in order to keep the human in the decision making process. However, ideal robotics solutions will attain better productivity, reduced cost and increased safety by relying on autonomous systems. Despite the considerable amount of research, deploying an autonomous robotic system inside a glove box is not feasible with current technology; however, certain parts of the task execution can benefit from autonomy or semi-autonomy.

Regardless of teleoperation or autonomy the area is cluttered, and the robot can not risk hitting the windows and breaking containment. This then requires the robot to be able to sense its location and environment and then avoid collisions.

Within teleoperation this primarily will present itself as a complex operation to be able to manage redundant joints re-orienting in the null space, risking collisions or reducing manipulability. The cognitive load of managing these additional degrees of freedom is very mentally taxing on the operator.

Beyond this, the limited number of sensors, and cluttered environment, thus leads to limited visibility. This then effects the ability of intelligent systems to act within the system.

The variety of tasks, events, and elements that the robot may encounter are numerous and unpredictable. For example, the faults that the robot may encounter can not be predicted, as testing for them through accelerated destructive testing would be prohibitively difficult. Similarly, an autonomous grasping system would be able to have a priori items that it can deal with, but many items such as shrapnel from decommissioning will be novel, possibly even in their physical characteristics.

The next issue is in assurance. The robot and must meet nuclear regulator and site owners requirements. The safety and operation must be verified and validated. This doesn't preclude advanced techniques such as deep learning, as verification through statistical methods have been used in nuclear []; but, it is a consideration.

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3. Previous Work

In the last forty years, the robotics research community has investigated innovative robotic solutions to improve the safety and the efficiency of operational activities in nuclear environments. In [2], the authors highlight the importance of robotic solutions to accomplish inspections and decommissioning tasks in a hazardous environment and glovebox, in particular, this aspect was investigated more in-depth with preliminary experiments in [3], where a robotic manipulator was exploited to dismantle a JDPR reactor. Autonomous robot and tele-operation are also key factors to innovate a legacy glovebox that is going to be dismantled in multiple nuclear facilities in the world. Up to now, operators accomplish different tasks by inserting the hand (with proper equipment) in a hazardous environment where the consequence of an accident could be serious: the operator could be contaminated by accidental cuts of the rubber glove [4] or by an error in operation process [5]. Robotics and artificial intelligence can be profitably used to remove the operator from dangerous tasks while autonomous or semi-autonomous systems could accomplish the activities. To pursue this aim, it is necessary to improve the control strategies of manipulation systems in order to operate in complex environments with constraints and robot redundancy [6].

One preliminary study into the use of automated robotics within a glovebox is presented in [7], where an automation system and non-redundant robotic arms are proposed to mitigate human operator risks in handling activities. In order to reduce operational cost, robotic solutions are proposed to execute ad-hoc tasks [8,9] and simulations are developed to aid in mitigating hazards that may be introduced as a result of the deployment of robotic manipulators [10]. The solutions proposed above are not multipurpose because they are designed to solve specific tasks. In this scenario, redundant collaborative robots can potentially improve the system manipulation capabilities [11] as redundancy can be exploited to adapt robot poses, for example, to avoid collision with objects in the constrained space, or to handle an object with higher quality grasping index [12], and, therefore, more robust handling. At the same time, novel strategies need to be designed to exploit redundancy within individual applications or tasks with the aim to reduce the control complexity.

The same strategies could support the operators in manipulation and grasping tasks that are accomplished with difficulty by tele-operation inside the glovebox, as shown in [13] or in [14].

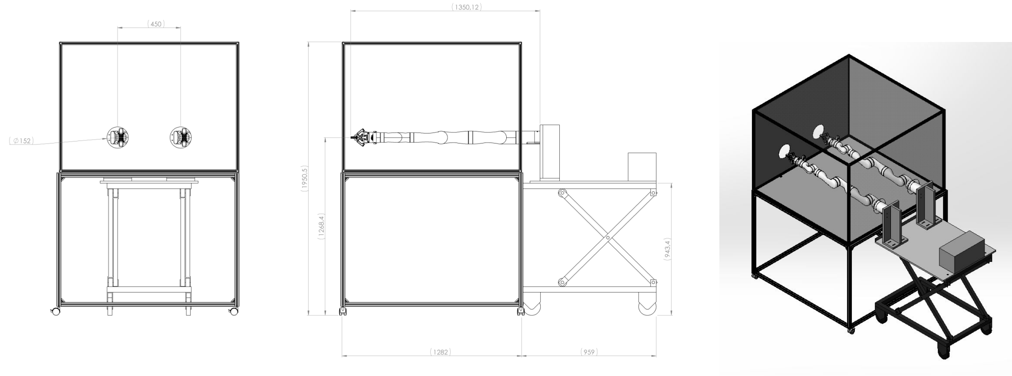

Figure 3. The glovebox mock-up hardware. The dimensions of the glovebox mock-up is based on legacy gloveboxes which are still being in use.

While a training course could improve the ability in manipulation tasks [15] and reduce the fatigue, in some cases an autonomous system could provide aid to the operator [16] to control the robot at any level of autonomy.

More recent research fields explore how to reduce the operator workload with high-level instructions given to the robot by voice command [17] while the usability of a humanoid robot is explored in order to do bi-manual tasks inside a legacy glovebox [18, 19]. In general, all the solutions, which are cited above, exploit methods and strategies presented in robotics literature in order to identify reliable grasping poses.

4. The RAIN Solution: Tele-operated robotic manipulation

The following is a proposed testing framework for glovebox robotics. It does not attempt to represent the challenges of contamination, but does attempt to reproduce in a safe environment the other challenges presented in Section 2.

4.1. Hardware

To best represent a human-like kinematic chain it is proposed to use a serial robot with inline joints, with a narrow diameter to fit through the glovebox ports. To limit possible forces exertible on internal surfaces a cobot is desirable due to in-built force limitations. This leads to the proposed option of the Kinova Gen3. The robot will be in-glove and the end-effector be in glovebox. This will allow for the end-effector to perform high dexterity task while minimising contamination, it also enables the possibility for tool changing. Two robots are mounted at a standard port width of 450mm on a mobile plinth that can be raised and lowered.

The Kinova Gen3 has a wrist mounted RGB-D camera. Then 2 external sensors are installed, RGB-D cameras, their positioning is subject to the operation being tested. All of this integrated with ROS and MoveIt [20], to deliver path planning, collision avoidance, tele-operation, and visualisation.

The glovebox mock-up itself is an aluminium extrusion frame, with an enclosed upped section with closed panels, and a support structure, as illustrated in Figure 3.

4.2. Simulator

An important asset for development and testing is a simulator, as it allows simpler, safer, faster, repeat testing without risk to humans or robots. For this reason a Glovebox Robot simulator was created [21].

The simulator has been generated in Gazebo and integrates the robots, the glovebox, and sensors. They have the same API for control and Moveit through ROS as the real robots. Additionally some tools in python have been generated to enable easy scripting of scripting. Two versions of the simulator have been generated: ROS package[1] and Docker container[2]. The docker option is essentially the same as the ROS package, but does not require installation, can start with a single command and has an entirely browser-based interface with gzweb for visualisation and Jupyter notebooks for interaction.

5. Research Areas

5.1. Autonomous grasping

As with all remote handling tasks the robot most do more than inspect, it must be able interact with the world. This may be using specially designed remote handling tooling enabling mechanical automation to simplify tasks. But eventually the robot will need to handle objects. This may be achieved through tele-operation. However, for performance and repeatability it would advantageous to have an autonomous method.

The glovebox presents a few abnormal issues in respect to the state of the for autonomous grasping. Firstly, is the constrained and cluttered environment which limits robot motions, and causes some optimal grasps to become unreachable. Then, there is the nature of the objects to be grasped. If they are known, they maybe damaged or contaminated, leading to them being desirably picked up from very particular points, with optimality and success rates regrading away from those point. Alternatively, many of the object in the boxes maybe entirely unique and novel in gloveboxes, with humans having not performing detailed inspections in 30 years. For this reason the system should also be capable of coping with a clutter of novel objects, that will need to be sorted in to be sorted in to different waste streams, for example.

5.1.1. Grasp synthesis

Operations in glovebox require to manipulate objects and tools in order to follow complex procedure, in this context it can be concluded that grasping plays a fundamental role to ensure safe and successful operation. Identifying a feasible grasp in a unstructured environment is one of the fundamental research question that is yet to be solved. The synthesis of a reliable grasp is complex because of (i) considering the geometric constraints (such as obstacles in the environment, the glovebox boundaries) on the arm/gripper pose, (ii) identifying a suitable grasp pose on the manipulated object and(iii) applying a suitable contact force distribution for a safe hold. In order to provide reliable solution for the problem described above, autonomous grasping strategies have to be improved to provide novel tools to support operator to identify feasible grasping poses or to develop robotic glovebox with high degree of autonomy.

Grasping synthesis in a glovebox, in robotics literature, could be formulated as as problem to identify feasible grasping solutions in a constrained workspace. Two different strategies are commonly used in order to identify feasible grasping poses that satisfy the environmental constraints: (1) finding grasp poses without considering constraints and then filtering them to respect environment constraints [22–25], (2) modelling the constraints inside the algorithm to find grasping poses [26–29].

Taking in account a priory knowledge of the proprieties of the object, the first group could be split in two different subgroups that use two different approaches based on: i) the model of the object or ii) sensor signals to partially estimate object properties

Several strategies have been proposed to identify optimal grasping poses in environments without constraints. If the object model is available, swept volumes and continuous collision detection [30] or independent contact region algorithms [31] are proposed to identify a handling pose. Force closure [22] and form closure index [32] optimisation could be considered a valid offline method to collect high quality grasping poses. In [23] a real-time algorithm is proposed to collect stable grasping poses.

[1] https://github.com/ukaea/Glovebox-Simulator
[2] https://github.com/ukaea/Glovebox-Simulator-Docker

In [33,34] the authors design an optimisation algorithm in order to identify suitable grasping poses taking into account optimal contact force distribution constraints. The environment constraints and hand kinematics are not considered in this work. A different approach is presented in [35], where support functions and wrench oriented grasp quality measures are used; this solver is not tested in a real scenario where a cluttered environment restricts feasible grasping poses.

5.2. Grasping without Object Model

The object model could be not available in all the scenario, in these cases sensor data are exploited to estimate some properties of the scene, then a partial reconstruction of the object is used to identify grasping poses.

One possible approach exploits a grasp quality neural network that is trained with information from a synthetic data set and RGB-D images; grasping pose candidates could be estimated in real time as shown in [36,37]. Usually, good performance is only achieved after extensive neural network training with a very large dataset.

Different light conditions and partial views of the scene could reduce the performance of these methods; in such condition Gaussian Process Implicit Surfaces and Sequential Convex programming could be used to recover the performance as shown in [24]

Alternatively grasping strategies could be inspired by human motor control, tactile sensor could be used to implement human inspired grasping strategies as shown in [25] or video recording of human handling sequence could be used to train the robot [38].

5.3. Grasping in Constrained Environments

Filtering grasping poses by constraints has the disadvantage that high quality grasping poses could be not identified, an alternative approach could be used to model the constraints directly in the research algorithm. Following the concept above, in a constrained environment reliable kinematic chain configurations are identified by minimizing a suitable cost index, the optimisation is subject to linear and nonlinear constraints, and is presented and tested on humanoid characters in [39,40].

A similar approach, for robotics applications, is provided by Graspit! [26] an algorithm that synthesize stable holding poses in constrained environments by exploiting simulation and shape primitives.

In a structured scenario the environment could be modelled and an accurate simulation tool can be developed using multi-body dynamics tools in order to avoid collision [27]. A complete knowledge of the workspace could be useful to avoid collisions between the robot and the objects as shown in [41] exploiting motion constraint graph.

In some hazardous application it's mandatory to guarantee a safety distance of the gripper from dangerous object in the scene, in these scene it's possible to use e a list of grasp candidate associated with a metric [28]. In order to identify feasible grasping poses in glovebox environment, a constrained optimization is proposed in [42], this method allows to synthesize poses of the manipulation systems that are force closure and are not in collision with glovebox walls.

Visual feedback could be a valid alternative, in unstructured environment, to evaluate the constraints and object positions that are necessary to plan grasping poses [29] or to move obstacles in order to reach a target object.

5.3.1. Grasp detection using deep learning

Advancements in deep learning models, especially in computer vision, has led to its widespread application in robotics and has been gaining popularity in autonomous operations. One of the limitations of this approach is that its performance is tied to the quality of the data, which is sometimes difficult to acquire. For an active agent in a dynamic environment, these data driven models can become challenging to implement where accuracy and speed are essential part of ensuring safety in operations. In recent years however, significant progress has been made for vastly improved levels of speed, accuracy and generalization that makes it possible to apply these models for a closed loop control system.

Robotic grasping is a difficult problem to solve due to the many sources of potential uncertainties such as object pose, shape, friction, camera pose [43]. Nuclear industry gloveboxes include the added challenges of limited visibility, clutter and objects with varying shapes and textures. In such cases, where finding an accurate model of the physical properties is difficult, data driven approaches have demonstrated that a level of adaptability can be reached when the robots learn from example.

5.3.2. Grasp estimation with convolutional neural networks

There has been many different approaches with deep neural networks on the grasp detection problem. Instead of a separate module to extract object properties, and using that output for further processing for extracting grasp information, these models estimate the grasp pose directly from the input data. While some models directly estimate 6dof gripper poses from 3D inputs such as pointclouds, others estimate 2D gripper poses from depth or RGB images and project them to 3D space. The availability of standardised grasp datasets such as Cornell [44] and Jacquard [45] and its relative speed of detection has made the 2D input models a popular choice for application in robotic grasping. These 2D input models can also be categorised into the type of outputs. The earlier models generated a 6 dimensional vector that represented the position, angle and width of a parallel plate gripper [46–48]. Models such as the Grasp Quality Convolutional Neural Network(GQ-CNN) [43] performs grasp sampling, followed by a grasp quality evaluator model which ranks the sampled grasps. In recent developments, the grasp map estimator type of models such as the Generative Grasp Convolutional Neural Network (GGCNN), first proposed in [49] has demonstrated the highest performance in terms of speed and accuracy. These networks, which generally follow an encoder-decoder structure of image segmentation maps, generate 2D maps associated with position, angle and width, with a pixelwise grasp representation.

5.3.3. Grasp convolutional neural network with Variational Autoencoders

For autonomous grasping in a glovebox, it is important to identify feasible gripper pose for novel objects in cluttered environment. For this purpose, a neural network was developed where a variational autoencoder (VAE) was added to a grasp map estimator type of model.

The VAEs, first proposed by Kingma and Welling in [50], maps the data into a distribution, also known as the latent space, from which samples drawn can generate data similar to the input. A VAE consist of two neural networks, respectively the encoder and the decoder, and a loss function. The encoder maps the input sample into a reduced size space, called latent space, containing the main characteristics of the sample. The decoder, in a similar way, maps back out from the latent space to the original form. The distinctiveness of a VAE is that the latent space has a form of Gaussian distributions, expressed as mean and logarithmic variance value. The loss function is given as the sum of two components: reconstruction loss and latent loss. The former measures the ability of the VAE to reconstruct in output the presented input, while the latter is a metric of how much the latent space is in form of Gaussian distribution.

In the proposed models, variational autoencoders were used for modelling the grasp estimation neural network. Two different types of VAEs were explored in this work, Conditional variational autoencoders (CVAE) [51] and Vector Quantized Variational Autoencoders (VQVAE) [52]. Similar to other grasp map estimation models such as [49,53], these models are also very lightweight and are able to generate grasp poses with relatively high speed. Evaluation of these approaches on the Cornell dataset also demonstrated a high grasp detection accuracy. These models were also evaluated with

3D models of objects with complex geometry such as the Evolved Grasping Analysis Dataset (EGAD)[54].

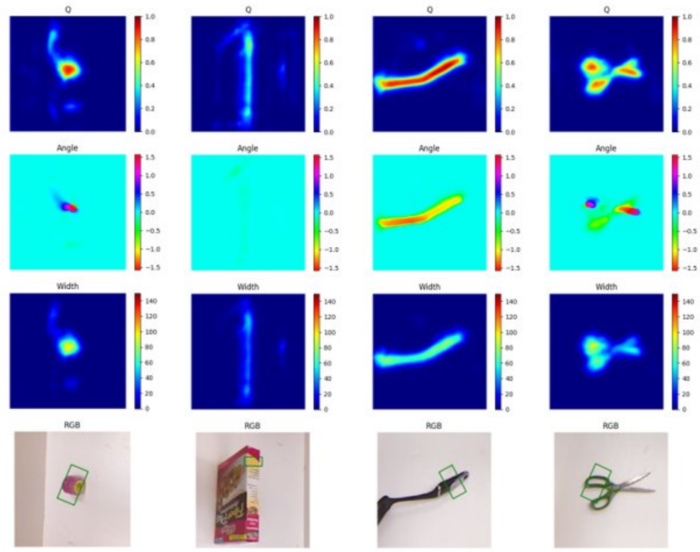

Figure 4. Grasp detection from the grasp quality, width and angle maps generated by the VQVAE grasp model on test images from the Cornell Dataset

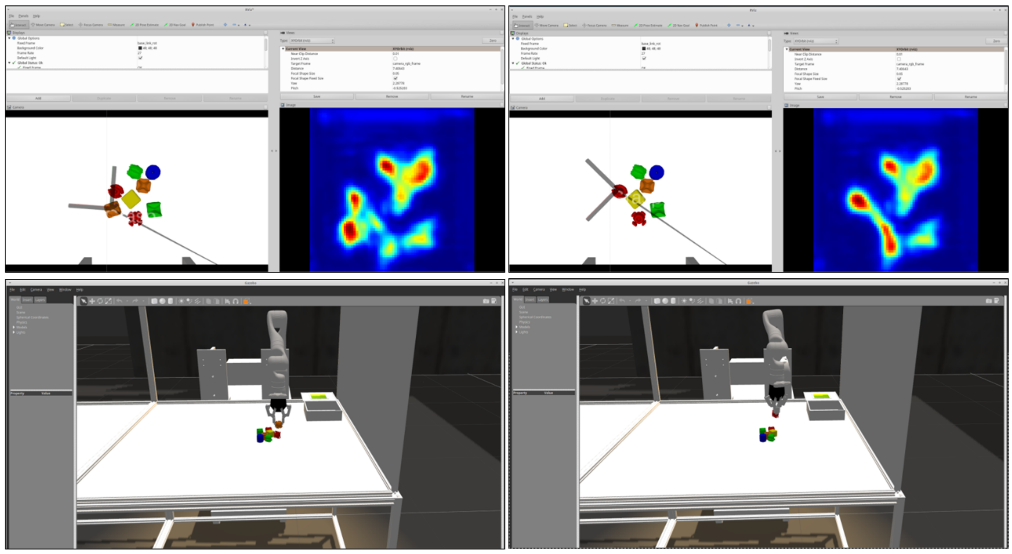

Figure 5. Grasp evaluation in simulation for cluttered environment with objects from the EGAD dataset. The top two pictures from RViz show the image and the estimated grasp map.

While grasp models reinforced by a VAE has shown promising results, the full extent of its capabilities are currently being investigated with in simulation and real world trials. Further improvements can be potentially introduced with its application on 3D input. Future work will include data from the simulation environment to train deep learning models to learn grasping pose directly from 3D data.

5.4. Assisting the operator

Nuclear decommissioning requires material-handling inside radioactively contaminated gloveboxes [14]. Working inside gloveboxes is not only dangerous for the operators, but also strenuous. These strenuous tasks performed inside the glovebox typically include cleaning, swabbing, removal, scrapping, *et cetera*, termed as Post-Operative

Clean Out (POCO) as they are done to clean previously functioning gloveboxes to make them fit for disposal. This work introduces robot manipulators inside the nuclear gloveboxes so that the different glovebox tasks could be remotely handled using teleoperation [7].

Introducing a teleoperated robotic system into gloveboxes ensures the safety of the operator by detaching the operator from the hazardous glovebox environment. However, the resulting manipulation system is, usually, not intuitive to use and requires certain level of familiarisation with the technology via extensive training in order to achieve effective use.

The teleoperated glovebox system improves the safety of the operator but the safety of the manipulation is not ensured by default. During the manipulation, the operator cannot omit the risks involving the robot and the environment and, therefore, the operators have to pay the utmost attention on the movement of the robotic arms, consider the possible collision scenarios and ensure the safety of the manipulated objects and the environment. Overall, the task load on the operator during a teleoperated manipulation is significantly high.

The RAIN project not only improves the safety of the operator, but also aims to improve the safety of the manipulation while keeping the task load on the operator as low as possible. Using a teleoperated robotic solution inherently implies the required operator safety; however, the safety of the operations, such as ensuring safe manipulation of objects in the glovebox and avoiding collision which might damage either the robot or the integrity of the glovebox components, is the fundamental question of this research package.

The teleoperated robotic system in the RAIN project allows the operator to plan and execute the manipulation in the task space of the robot using an intuitive interface at the local (operator) side. Well-known tele-robotic solutions, such as Mascot system used in Joint European Torus, provide two kinematically similar robotic interfaces for the tele-manipulation to achieve a simplified control architecture and allow operators to control robots at the joint level. While this approach can be viewed as giving operators more controls on the robot, the resulting teleoperation system is more costly (due to the use of similar robots) and not always as intuitive as expected due to the kinematic structure of the robots. In order to achieve a cost effective solution with ease of use, the teleoperation system in RAIN gloveboxes are relying on local-remote devices with dissimilar kinematics where the local device is a hand tracking system while the remote robot is an industrial robotic arm.

The local device, an HTC Vive controller, is a vision based tracking system which closely monitors the pose of the operator hand. The tracking system introduces an unmatched level of intuitiveness to the robot control by allowing the operators to use the hand motion to drive the end-effector remote robot. The reference signal, which is the operator hand pose, is tracked by the low level motion controller of the remote robot of the teleoperator. The choice of allowing the operators to plan and execute the their actions in the task space of the remote robot is the first step in reducing the task load on the operator.

The intuitive control interface and the task space control approach is prone to unwanted collisions because there is not mechanism to prevent the remote robots from colliding with the environment or the objects. Therefore, without any assistance mechanism in the teleoperation, the resulting teleoperator would require the operator to ensure the safety of the operation.

The motivation for this work is to achieve a system which follows a given end-effector motion reference without colliding with the environment or the obstacles while keeping the manipulation capability of the robot as high as possible.

An exemplary setup is introduced in Figure 6 which depicts one of the remote robot arms with an obstacle inside the glovebox. The operator is expected to manoeuvre the robot while avoiding any collision with the obstacle; however, in the given robot

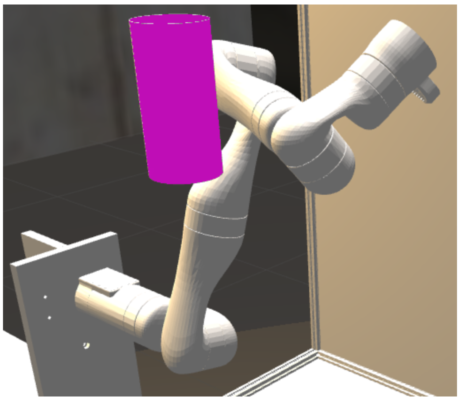

Figure 6. Remote robot colliding with an obstacle in the glovebox interior.

configuration, the elbow of the robot is likely to collide with the cylindrical object. Instead of relying on the operator skills for avoiding collisions and securing the operational safety, our approach utilises the redundancy available in the remote robot and implement a collision avoiding rule to the inverse kinematics solutions of the robot. Hence, the proposed approach still enjoys the task space planning and control of the robot arm during the tele-manipulation and the collisions are avoided at the inverse kinematics solutions.

Obtaining the joint space motion synthesis from a given end-effector trajectory is a challenging problem due to the inherent nonlinear relation between the joint and task space positions. For majority of robots, this nonlinear mapping prevents obtaining analytical solutions to the inverse kinematics problem. As a result, numerical solution methods are popular for solving the inverse kinematics problem.

The inverse kinematics problem becomes more intricate for redundant robots, since the mapping between joint and task spaces become one-to-many: multiple joint space configurations are mapped to the same task space configuration. These multiple inverse kinematics solutions naturally vary with levels of optimality in respect to different performance measures, such as collision or singularity metrics.

The assisting the operator research package designs an inverse kinematics solution algorithm for the teleoperation of redundant remote robots. In this approach, the joint space trajectories, which are required to control the remote robot, is generated from the operator motion reference. The inverse kinematics solution simultaneously considers the collision of the robot arm with the objects/obstacles in the environment and improve the manipulability of the remote robot configuration for better manipulation.

Manoeuvring the teleoperated manipulators in a cluttered environment and/or a confined space is a well established problem in the robotics literature [55]. The likes of [56–58] have addressed the problem of collision detection and trajectory generation for moving the manipulator through the clutter. However, the problem becomes more complicated when the space where the whole body of the manipulator will move becomes restricted due to scattered clutter. This situation is explained in the following example.

Figure 7 depicts a manipulator inside a confined space and the end-effector of the manipulator needs to reach to particular objects amidst a bunch of different objects inside the space. It should be noted that, in addition to the end-effector, the links of the robot can collide with the objects in the glovebox. Then, precise trajectory estimation can facilitate to avoid catastrophic accidents. In this work, we are addressing the collision detection problem and primarily focusing on collision detection and avoidance of teleoperated robots inside nuclear gloveboxes.

Avoiding collisions is important for safe operations; however, smooth manoeuvring the remote robot is another important step for reducing the task load on the operator.

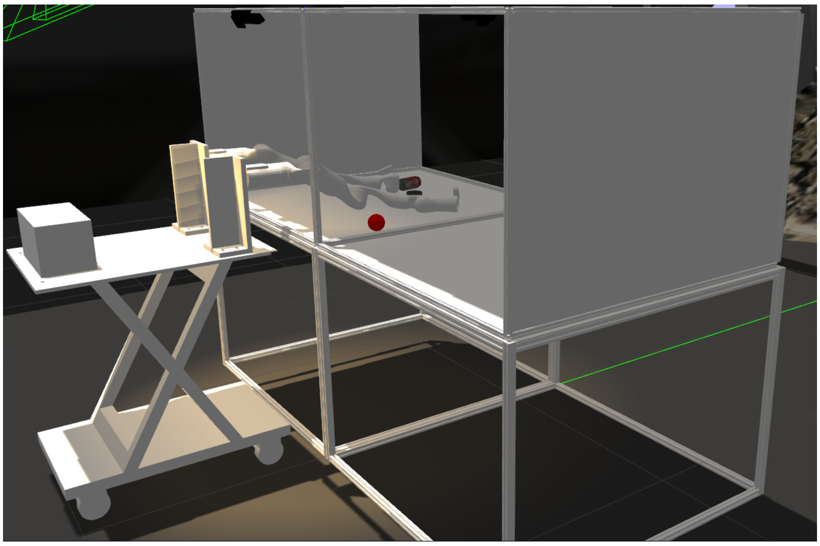

Figure 7. Glovebox simulator built in the ROS/Gazebo environment. The simulator depicts the remote robot arms, glovebox and obstacles for manipulation.

The ability of moving the robot end-effector in arbitrary direction is characterised by the manipulability of the robot.

5.4.1. Augmenting sensing

The challenges of working with gloveboxes also extend to poor visibility caused due the combination of discoloured and damaged windows, dark and cluttered environment and wearing of personal protective equipment which usually limits the field of view for the operators. While the introduction of a simple camera view of the interiors can be useful, additional information related to the environment properties such as the type of objects, its position and pose, would not only provide helpful guidance during teleoperation, but also form an important component for grasp estimation and collision avoidance systems.

For the glovebox computer vision, multiple sources of visual information were acquired through RGBD and stereo cameras and different processing units were developed to extract valuable information about the environment. In addition to the static sensors, the RGBD wrist cameras attached to the Kinova robots were used for surveying the less accessible areas. The vision modules include object detection and tracking, semantic segmentation RGB image, grasp detection and pointcloud segmentation.

Deep learning models were trained using custom annotated images that are representative of a glovebox environment. An object detection network was trained with the dataset from which, the output detection were then fed into a tracking algorithm. For objects detection, a models similar to the You Only Look Once (YOLO)[59] were chosen since they generated detection at a much faster rate. In addition, a scene segmentation model was also implemented to extract more detailed information about the environment. These models provide a pixel-wise categorisation of the image. Models such as Deeplab [60] demonstrated high accuracy, but had a much slower response time. The segmented objects were projected to 3D to extract segmented pointclouds. This technique was used mainly for estimating the object shape and pose of known objects and obtaining an initial map of the environment. While these supervised techniques for object detection and segmentation, have demonstrated high accuracy on the training dataset, there is less room for improvements in terms of generalising for novel objects. The grasp detection model was kept independent of object recognition and is able to detect grasping pose objects regardless of its type.

Unsupervised detection, which includes traditional computer vision techniques, was also introduced to extract objects with simpler geometries such as cylinders, cubes and spheres. The PCL library [61] was used for pointcloud segmentation which implements a RANSAC [62] based technique to extract object position, orientation and size. This information was the input for the Grasp synthesis module, (described in section 5.3), which then generated optimal grasping pose for the objects. The extracted objects were also introduced into the simulation platform, which is useful for testing of the algorithms before deployment.

5.5. Condition Monitoring of the Robots

In a robotic glovebox it is extremely important to have confidence that the robot will not occur in any failure during operations. Such failure can have dramatic impacts both on safety and on costs. A robot unable to be properly controlled can have catastrophic consequences, for example it can impact on glovebox's walls and damage it. Also, a robot which is not able to move can be difficult or impossible to retrieve and repair with a big impact on costs in terms of both hardware costs and time delay.

A Condition Monitoring System (CMS) has the objective of monitoring robots measurements and identify any anomalous behaviour.

In recent years many deep learning techniques have been used to identify anomalies in many different environments, from images to bank transactions. In this work we focused our attention on Variational AutoEncoder (VAE) (see section 5.3.3).

In this work we applied VAE model to a set of automated moves we perform specifically for CMS as part of our operational routine. They are performed at the beginning and at the end of operations, in order to inform the operator that the robot is respectively safe to use or has not been damaged during the session.

As already mentioned earlier, our glovebox consists of two identical Kinova Gen3 robots equipped with different end effectors. We have used data collected from only one robot, from now on training robot, and used data collected from the other robot, from now on testing robot, only for testing purpose.

In order to capture the dynamic behaviour of the system, we considered as a single sample at time t_{now} all the measurement collected in the interval $[t_{now} - TIME\_WINDOW; t_{now}]$. It is important to note that this does not effect the ability of the system of working online. Also the length of the interval has an effect on the ability of the system capturing information and therefore identifying different types of anomalies.

In Figures 8, 9, and 10 it is possible to see how the trained VAE is able to reconstruct measurements collected from CMS moves. For simplicity we will report in our pictures only on reconstruction of joint 3 in few time intervals. In particular Figures 8 and 9 show actual measurements and their reconstruction in case of respectively data collected from the training robot included in the VAE training set and data collected from the training robot but not included in the VAE training set. It is possible to note that the VAE is correctly reconstructing the measurements.

Similarly, Figure 10 shows actual measurements and their reconstruction in case of data collected from the testing robot. It is clearly visible that in some time intervals the VAE is not able to correctly reconstruct the measurements. These time intervals should be considered as anomalies. We believe that this anomalies are due to the different end effector installed on each robot.

Figure 11 show the VAE score of each sample of a CMS move in the three cases before, i.e. data coming from training robot included in VAE training set, data coming from training robot not included in the VAE training set and data collected from the testing robot.

5.6. Operations

The Operations Management System (OMS) is a web application that supports the three main facets of operations: management of the assets used or encountered during an operation, preparation of the operational procedures to be carried out, and the execution

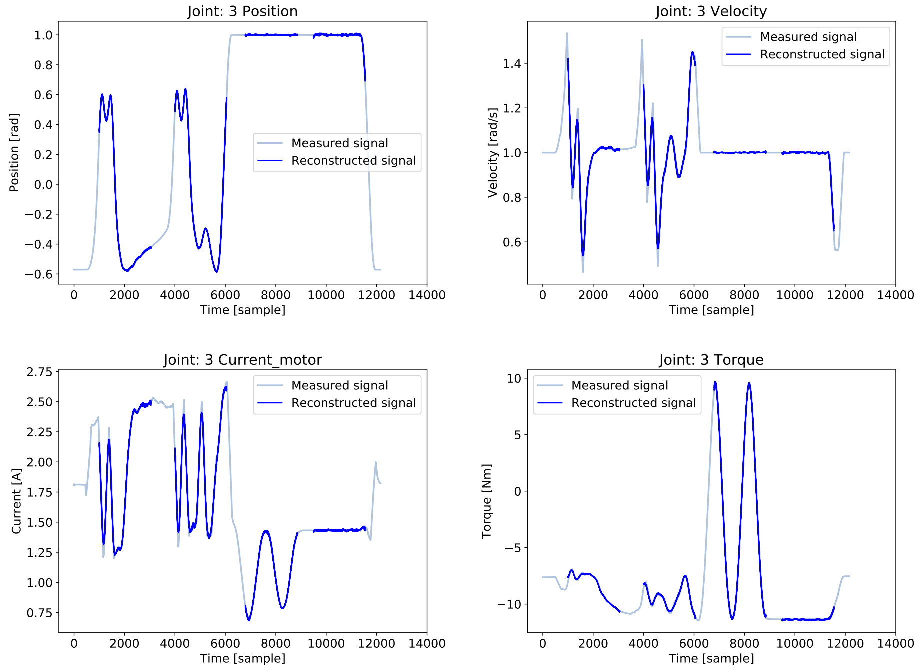

Figure 8. Example of data reconstructed by VAE in case of data collected from the training robot and included in the VAE training set. In light blue are reported original measurement, while in dark blue are reported different sample of reconstructed output.

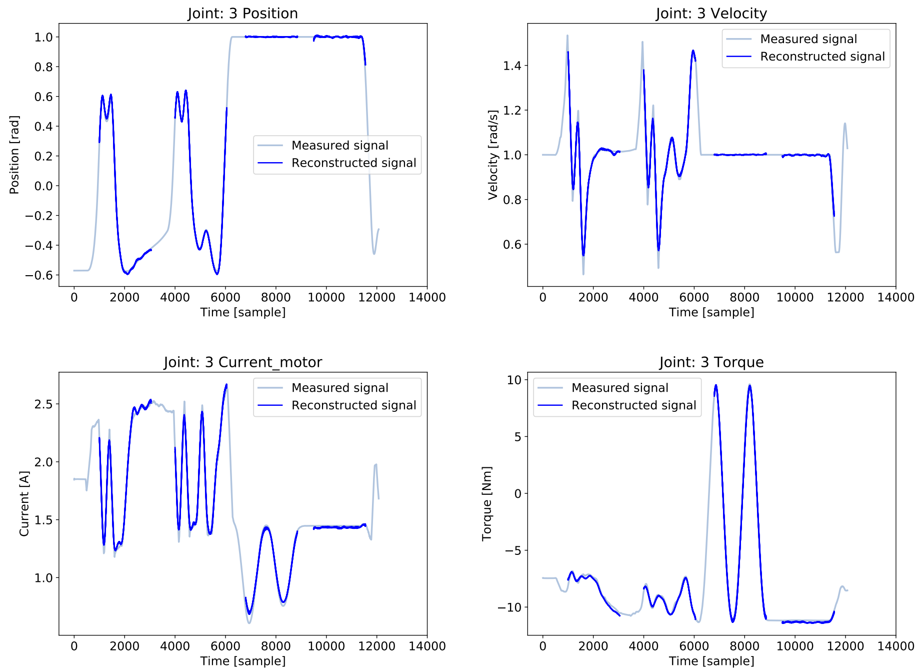

Figure 9. Example of data reconstructed by VAE in case of data collected from the training robot but not included in the VAE training set. In light blue are reported original measurement, while in dark blue are reported different sample of reconstructed output.

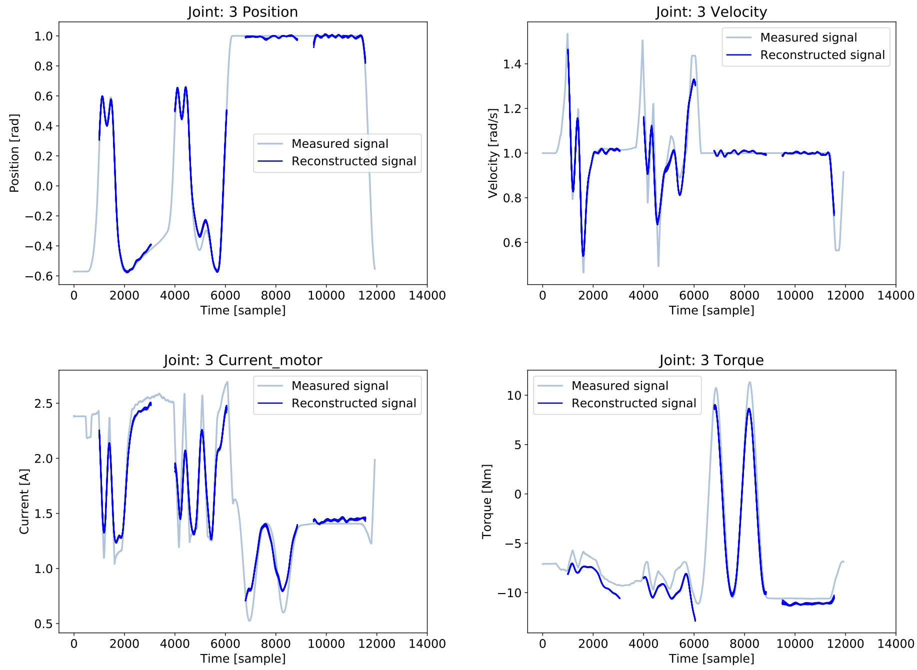

Figure 10. Example of data reconstructed by VAE in case of data collected from the testing robot. In light blue are reported original measurement, while in dark blue are reported different sample of reconstructed output.

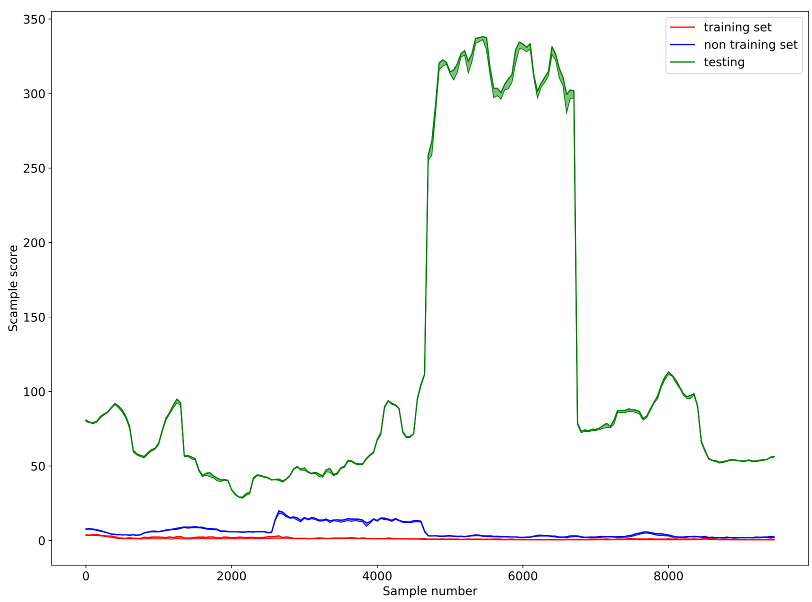

Figure 11. Example of VAE score evolution over time for the following three cases: data collected from training robot and included in the training set (red line), data collected from training robot but not included in the training set (blue line), and data collected from the testing robot (green line)

of those operational procedures. Built off 35,000 hours of remote handling operations at JET, OMS is a unique operations management tool.

In particular, RAIN intends to use the planning and execution capabilities of the OMS application to reduce cognitive load on the operator by the following means. Firstly, an in-built capability of procedures in OMS highlights a single action or decision at all times as the current operational activity to be addressed, with progression being tracked throughout the procedure, including along any sub-procedures or different branches resulting from decision points. Secondly, the planned procedures often give the operator the choice of completing the action via teleoperation or else allowing the robotic system to autonomously complete the action by submitting pre-configured commands through OMS.

6. Conclusion

Nuclear gloveboxes are designed for safe handling of hazardous objects. The safety measures, personal protective equipment and the glovebox construction provide some degree of assurance to the operators. However, they are still prone to hazards and working conditions are still challenging given the long working long hours in a glovebox which is an arduous task.

In RAIN project, we are introducing and developing cutting-edge robotics and AI technology to the legacy gloveboxes for improving the safety of the operator and operations, along with ease of operation. Moreover, our approach potentially increases the efficiency in handling nuclear materials inside gloveboxes. The technologies we develop are automated grasping for robotic manipulators working inside the gloveboxes, assistive teleoperation technologies for easing the task load of the operators using the developed robotic glovebox solution and condition monitoring the robots for the early detection of failures in the robot hardware.

The technologies developed and integrated into the gloveboxes is a step forward for safer and more efficient manipulation interfaces for handling nuclear materials and contaminated objects. Furthermore, the next generation gloveboxes will be based on these technologies.

Author Contributions: Conceptualization, G.B. and R.S.; autonomous grasping A.A.; grasping in constraint environments R.N.; assisting the operator O.T. and P.D.; condition monitoring of the robots L.P.; writing O.T, P.D., R.N., L.P., A.A., G.B.; supervision G.B. and R.S.; All authors have read and agreed to the published version of the manuscript.

Funding: This project has been supported by the RAIN Hub, which is funded by the Industrial Strategy Challenge Fund, part of the government's modern Industrial Strategy. The fund is delivered by UK Research and Innovation and managed by EPSRC [EP/R026084/1].

Institutional Review Board Statement: Not applicable

Informed Consent Statement: Not applicable

Acknowledgments: Authors thank Emil Jonasson for his contributions.

Conflicts of Interest: The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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