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Human Robot Interaction for Future Remote Manipulations in Industry 4.0 ⋆

Ayan Ghosh, Daniel Alonso Paredes Soto, Sandor M Veres and Anthony Rossiter

The University of Sheffield, Sheffield, S1 3JD United Kingdom (e-mail: ayan.ghosh/ d.paredes-soto/ s.veres/ j.a.rossiter@sheffield.ac.uk).

Abstract: In the nuclear industry it is still common to rely on tele-operated robots. Teleoperation however can be strenuous and demanding on operating personnel and productivity can be low without advanced HRI interfaces. Today, the world is moving towards Industry 4.0. With that vision, this paper introduces the concept of Remotely Instructed Robots (RIRs), which are reliable yet rely on human intelligence. RIRs can accept high and low level instructions from the operator and execute tasks based on operators' descriptions and at a variety of complexity levels. The paper outlines an agent model of RIRs and furthermore, presents how it could be implemented inside nuclear gloveboxes to achieve novel human robot interaction.

Keywords: Safe Human-robot Interaction, Industry4.0, Remotely Instructed robots, Digital twin

1. INTRODUCTION

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 (Talha et al., 2016b). Intelligent use of remote handling techniques (Aitken et al., 2018) can facilitate safe decommissioning at nuclear sites when the levels of radiation are above acceptable limits. To date, robotic systems, AI, virtual reality and other advanced technologies for remote handling have had very little impact on the industry, even though it is clear that they offer major opportunities for improving productivity and significantly reduce risks to human health. As the main objective is to increase productivity, reduce operator strain, improve safety by reducing the chance of human exposure to radiation and other hazards, the nuclear industry has been taking initiatives to bring in innovation along the lines of Industry 4.0 [1].

As safety is paramount, semi-autonomous operations are slow in uptake in the nuclear industry. It is still common to rely on teleoperated robotic systems. Teleoperation, can however be strenuous on operating personnel and it requires high volumes of training.

Industry 4.0 encompasses a paradigm shift towards smart operations (Thoben et al., 2017), where humans are not to be replaced by artificial intelligence, robotics and automation, rather *"their capabilities are to be enhanced by smartly designing customised solutions"*. Therefore, within the context of Industry 4.0, industrial applications in nuclear need to be smarter, as they do in smart manufacturing (Davis et al., 2015). This will enable the processes to achieve higher levels of safety, improved productivity and reduced cognitive load of human operators, which are essential ingredients of smart technological interfaces in Industry 4.0 (Fig 1).

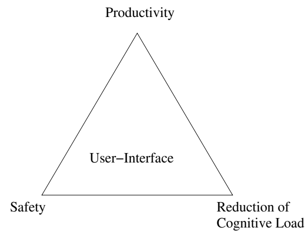

Fig. 1. The direct benefits of smart interfaces.

Symbiotic human robot interaction (Wang et al., 2015) is the key to a smart robotics environment in Industry 4.0. Smart robots and collaborative interaction integrate to form *Cyber Physical Systems(CPS)* Thoben et al. (2017) rightly mentions *"Robotic CPS can enable such human-robot collaboration with the characteristics of dynamic task planning, active collision avoidance, and adaptive robot control. Humans are part of the CPS design, in which human instructions to robots by speech, signs or hand gestures are possible during collaborative handling, assembly, packaging, food processing or other tasks."*.

Within the realm of robotic CPS for nuclear industry, this paper introduces the concept and an architecture for Remotely Instructed Robots (RIRs), which are distinguished from telerobots by higher abstraction levels of human instructions. A RIR is a mobile or stationary robot with material handling capabilities with arm(s) and can accept instructions by speech, gestures, VR interaction, etc. from its operators and execute tasks based on operators' descriptions at a variety of complexity levels. The RIR family can include intelligent glove boxes for the nuclear industry or warehouse robots that pick up and bring requested items. In principle, the aim of this paper

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[1] https://www.gov.uk/government/news/3-million-dragons-den-style-competition-shortlists-ideas-to-clean-up-old-nuclear-plants

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is to strike a balance between autonomy and intelligence (Heyer, 2010) of the human operators. The paper also presents novel human interaction techniques and effective communications via VR solutions.

2. AN AGENT MODEL FOR RIR

The agent model to control the RIR will be symbolized by the tuple $R = (P, A, C, K, D)$ where P stands for its perception, A stands for its actions skills, C stands for its communications skills, K denotes its knowledge representation and D denotes its decision making algorithms that use all of P, K to decide whether to perform some physical action by relying on A or doing a communicative act from C. The "mental state" of the the robot is implicitly defined by the data in its world model held in P and its knowledge in K that determines how it reacts to requests of its operator.

2.1 Perception data and processes P

In the proposed agent model R, the perception P is described by an ontology O_P for classes of data structures for the robot to model its environment. The defined data structures are used in signal processing from sensors in the robot's environment (such as cameras, lidar, etc.). A further process is for the robot to present its model of the environment to the human operator to facilitate receiving instructions via a smart interface.

Perception data The perception system of RIRs splits into three parts for HRI:

$$P = (O_P, M_P, D_P)$$

where O_P is the ontology of perception data, M_P is world modelling data with short term memory and D_P is a representation of the world model in a digital twin (Tao et al., 2018). Modelling and memory M_P contains the current scene model and its history in the past to reflect changes that the robot is aware of in terms of 3D graphs to reduce the amount of storage needed.

Perception processes Perception processes are computations that convert sensor data to perception data of the formats described above to result in M_P and D_P.

Perception representations Perception representations are an innovative feature used to inform the human operator of the RI robot about the robot's ability to "understand" its environment. The robot's model of its environment can be shown to the human operator, which can reveal possible misunderstandings as well it can confirm and hence raise operator confidence in the robot's work.

2.2 RI robot actions A

This paper calls steps of robot activities 'actions', which involve some physical movement of the robot, such as the robot moving to a new position, moving its arm into a required position, grasping an object, carrying/moving and placing an object, etc. A RI robot can also make moves to enhance the quality of its world model. Hence $A = (A_h, A_p)$ to indicate robot movements to interact with the physical world (A_h) and movements with the sole purpose of improving its perception model(A_p) of the environment. A challenge in the operation of remotely operated robots is to quickly and unambiguously communicate where to move and which object to grasp. This is an HRI challenge addressed in the rest of this paper via the human operators interaction with the scene view presented by the robot that reflects its current knowledge of the world it operates in.

2.3 RI robot knowledge K

A most basic ability of an RI robot is its ability to recognize a set of environmental objects or features that are relevant to its work. Another ability it needs is to have records about the physical and geometrical properties of the objects recognized. Finally, it also needs to be able to recognize damaging interactions between the objects in its scene model.

Examples of these are the ability to recognize that an object is not stable in its position, that its movement would damage other objects. For instance, it would recognize that the liquid in a container will flow out if it is knocked over.

2.4 RI robot communications C

RIRs are distinct from tele-operated robots and also from fully autonomous robots in a way that they can perform complex tasks and actions from abstract instructions by the remote operator, while they are not intended to perform long term goal oriented behaviour. The set of actions and tasks, which can consist of a sequence of actions, are limited to a predefined set of operational steps. This set of operations, each of which can be invoked by a set of instructions, is to be well known to the RIR's operator and clearly leaves the decisions, on what is the next action step to perform, with the operator.

Such an approach to robot control inevitably requires that the robots must always sufficiently inform the operators so that they can decide what to do next. As the robot is not equipped with complex goal oriented planning and execution, the best it can do is to provide the operator with as much information about the working environment as possible, and do that in an ergonomic way, which does not load the mind of the operator unnecessarily.

2.5 RIR's decisions D

Decisions by RIRs are limited to how to best perform an instructed movement or handling task and also on decisions about what information it is likely the operator would request to make a decision. If the operator were to be automatically provided information through most suitable 3D views of its perceptual model in the form of a digital twin, then the operator would not even have to issue past keystrokes based comments to ask for more detailed information and could instead proceed with fast keystrokes and pointing for robot movement and handling actions. The robot records all past activity in terms of changes of scenes and in data economic 3D graphs and recording of associated action requests in its memory. When a new scene is to work in then the memory is searched for similar situations and the average views requested are shown to the operator for a decision.

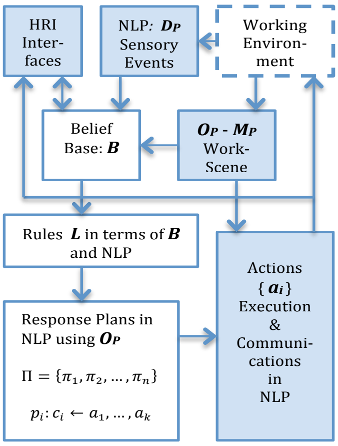

Fig. 2. Decision Manager Block Diagram

By a suitable analogy of AgentSpeak-like architectures (Lincoln and Veres, 2013; Wooldridge, 2009; Rao, 1996), in this paper we consider an agent decision manager as tuple:

$$\mathcal{D} = \{\mathcal{F}, B, L, \Pi\} \tag{1}$$

with

- $\mathcal{F} = \{p_1, p_2, \ldots, p_{n_p}\}$ is the set of predicates, also called beliefs.
- $B \subset \mathcal{F}$ is the total set of beliefs. The current belief base at time t is defined as $B_t \subset B$. Beliefs can be added, deleted or modified as *internal* or *external* depending on whether they are resulting from an internal action, or from an external input, including human input
- $L = \{l_1, l_2, \ldots l_{n_l}\}$ is a set of rules using of predicates.
- $\Pi = \{\pi_1, \pi_2, \ldots, \pi_{n_\pi}\}$ is a set of executable plans in the agent's *plans library*. Applicable plans are part of the subset applicable plan $\Pi_t \subset \Pi$ or "desire set" at time t.

The following three operations are repeated during each reasoning cycle of the HRI.

- *Maintenance of Percepts*: This means generation of perception predicates for B_t and data objects such as the world model.
- *Logic rules*: A set of logic based implication rules L, which describe reasoning to improve the agent's current knowledge about the world.
- *HRI Response plans*: A set of *executable plans* or *plan library* Π. Each plan π_j is described in the form:
$$p_j : c_j \leftarrow a_1, a_2, \ldots, a_{n_j} \tag{2}$$
where $p_j \in B$ is a *triggering predicate*, which prompts the plan to be retrieved from the plan library whenever it appears in the current belief base, $c_j \in B$ is a logic formula of a *context*, which helps the agent to check the condition of the interaction space, described by the current belief set B_t, before applying a particular plan sequence $a_1, a_2, \ldots, a_{n_j} \in A$ with a list of actions. Each a_j can be either a predicate of an external action (A_h) with arguments of names of data objects or internal action ((A_p)) with a preceding + or - sign to indicate whether the predicate needs to be added or taken away from the belief set B_t (3) conditional set of items from both.

Fig. 3. Typical Nuclear Glovebox

The reasoning cycle of our agent used in this paper consists of the following steps (Figure 2):

(1) *Belief base update*: The belief base is updated by retrieving information about the human-robot interaction space through perception and communication.
(2) *Application of logic rules*: The rules in L are applied in cycles (restarting at the beginning of the list) until there are no new predicates generated for B_t.
(3) *Plan Selection*: All the logic-triggered plans in T_t are checked for their context to form the *Applicable Plans* set Π_t, its elements denoted by π_t.
(4) *Plan Executions*: All plans in π_t are to be executed concurrently by going through the plan items $a_1, a_2, \ldots, a_{n_j}$, possibly under logical conditions within the plan.

3. USE CASE: RIR IN SMART GLOVEBOXES FOR NUCLEAR DECOMMISSIONING

In the previous section we defined an agen model of RIR. This section presents a potential use-case for the RIRs within the paradigm of Industry 4.0. The nuclear industry has been contemplating the use of smart gloveboxes for nuclear decommissioning in future. Gloveboxes are very commonly used within the industry (as shown in Figure 3) for treating nuclear waste, with current operational cost to be estimated over £10 million. Manual glovebox operations require personnel to put their hands in dangerous environments and as a result, they regularly come into close proximity to nuclear materials. This makes working within a glovebox particularly hazardous in terms of the potential risks to a human operator.

Due to the nature of the working environment within a glovebox, the levels of personal protective equipment required, such as gloves and possibly respirators, an operator's dexterity and task visibility is impaired. The environment within a glovebox can be restrictive and cramped, and the views provided by glovebox windows can be limited (as depicted in Figure 3).

These factors all contribute to making glovebox operation demanding. Due to the materials being handled within a glovebox, incidents (Rollow, 2000) that occur involving injury can have serious long term effects.

Within the glovebox environment, one of the biggest hazards to an operator is the puncturing of a glove. This can most commonly occur due to two possible causes;

sharp items, or items that have moving parts that can tear or shear the glove.For all these reasons, moving ahead with industry 4.0 and increase operational effectiveness, the nuclear industry has been looking to make smart enhancements [2] of future glove box operations in a way that operators can perform all the necessary operations from remote locations. With the advent of sensor technologies which could be placed or posted inside (depending on radiation levels), the way forward is to implement multi-joint robotic manipulators inside gloveboxes which are capable of being operated remotely through an intuitive and safe interface.

3.1 Related Work on Human Robot Interaction

The main uptake of the nuclear industry is tele-operated robots to carry out remote manipulations/glovebox operations and there are multiple existing solutions (Hokayem and Spong, 2006; Allspaw et al., 2018). Mostly hand held controllers are in use for various tele-operations (Rakita et al., 2018; Whitney et al., 2017), however recently, Jang et al. (2019) developed a hands-free *leap motion* based tele-operation system (Cancedda et al., 2017) where the operator's hand gestures are translated into movements of the robot. There also exist exoskeleton glove interfaces (Hu et al., 2005; Lii et al., 2010) with haptic force feedback to remotely tele-operate robotic systems.

It is important to note that when an operator uses the tele-robotic manipulator as a tool from a remote location, it functions as an extension of the physical body (Rademaker et al., 2014) and action space involves various psychological processes such as perception, attention and cognition (Seed and Byrne, 2010). It induces a spatial remapping and suggests a direct expansion of the so-called *peripersonal* space to the whole space reachable by the tool (Baccarini and Maravita, 2013). However, the glovebox operators work in shifts of 6 to 8 hours usually, and under such circumstances hand controlled tele-robotics can cause muscle fatigue (Nur et al., 2015) that has a direct effect (Kahol et al., 2008) on their cognitive load. Therefore, for achieving high productivity in interactions, we envisage implementing an RIR prototype in gloveboxes for effective HRI, which has the potential to improve perception of the operators and significantly reduce their muscle fatigue.

4. RIR IN NUCLEAR GLOVEBOXES

This paper introduced the concept of Remotely Instructed robots, which creates a balance between autonomous robots with a long term goal and tele-operated robots and in section 2 an agent model of RIR has been outlined. When these robots are implemented inside smart gloveboxes, they would rely on human intelligence and can accept high and low level commands (such as "*pick up object B and place it into container C*") from the operator and execute tasks based on operators' descriptions and at a variety of complexity levels. Basically the robot does not decide on its own that it has to pick up the *object B* and place into the *container C*. The decision is taken by the human operator and language based instructions are fed to the robot in the form of instructions. However, the robot needs to interpret those instructions and act accordingly. In our RIR system, a natural language based interaction, augmented with the virtual model of the robot (rendering the actual robot's status to form a digital twin) and its working environment are presented to its operator who can point to locations and objects within the virtual model to complement the verbal communication.

[2] https://www.gamechangers.technology/challenges/gloveboxes/

4.1 RIR Working Environment

A proof-of-concept RIR is designed for a glovebox prototype that enables a human operator to operate a remote robotic manipulator through high level instructions. The physical system for our proof-of-concept consists of a 6 DOF robotic manipulator (UR5) and a 3 finger gripper, placed inside the glovebox along with the sample set of objects, which are typically nuclear materials and complex in shapes and sizes.

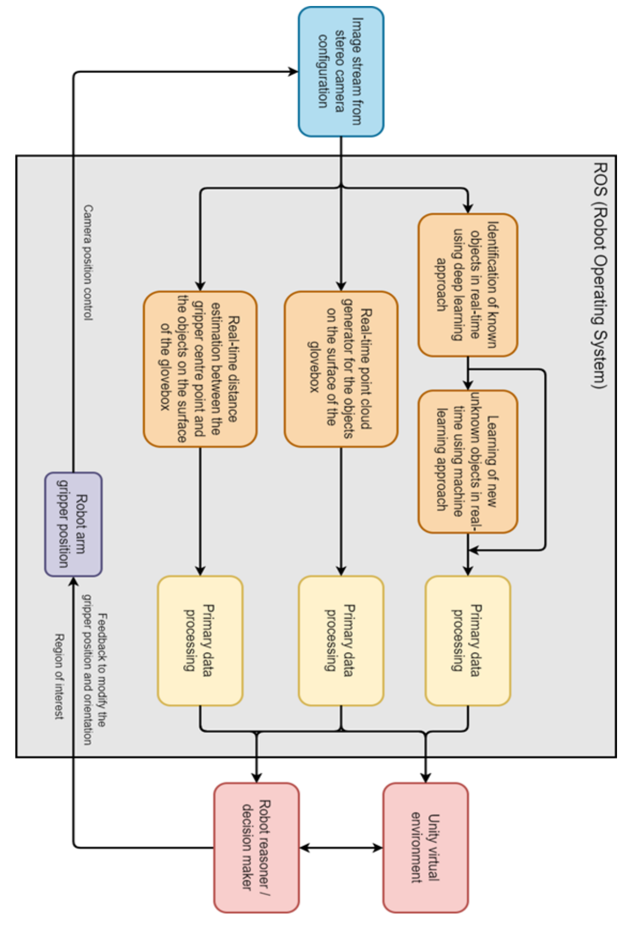

Fig. 4. RIR perception Process

4.2 Sensing and Perception inside gloveboxes

As mentioned in the agent model of a RIR, a key aspect is the robot's perception, on which the robot can plan its actions. A stereo vision sensor is fitted to the end effector of the robot to provide a continuous stream of images, as it scans its working environment. The perception system by default can detect and recognise *known* objects (objects are referred as known when they are a part of the dataset used to pre-train the object detection model), based on a real-time object detection pipeline along with their object poses. If any object is *unknown* to the system, it will give an indication to the operator to manually identify the new object and feed it to the the world modelling data stream so that it can be automatically recognised subsequently. Once detected, the system is able to estimate the distances between the gripper and the detected objects, generate a dense point cloud, segment the point cloud (Figure 5), convert the segmented point cloud into triangulated 3D meshes and apply object textures on those meshes. This environment reconstruction data is basically the representation of the world model, as mentioned in section 2.1. The entire process is depicted in Figure 4

As described in the agent model, the perception data is defined in the form of an ontology, which is a hierarchical description of data structures(Ghosh et al., 2020) and can easily be used to configure/reconfigure the perception process in future.

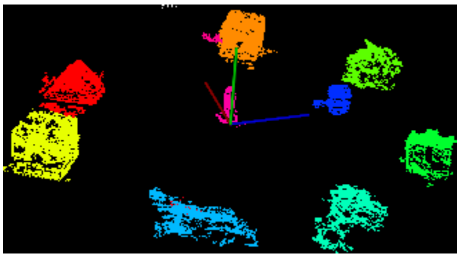

Fig. 5. Foreground object segmentation with a euclidean clustering algorithm.

4.3 HRI interface and Representation of the World Model

Another key aspect of any remote operation is that the operator needs situational awareness and clarity. This necessitates an effective visualisation of the remote environment. Authors of Talha et al. (2016a) highlighted that the workload of the operators increase, when they carry out remote tasks looking at 2D images from multiple views and they use these images to create a 3D mental model of the remote environment. King and Hamilton (2009) list some of the benefits of using 3D visualisation systems for remote operation. Therefore, for a better understanding of the work-space, a RIR system intends to present the complete 3D representation of the environment and a labelled list of objects present in the environment, together with the status of the robot in an ergonomic way. All this data is communicated to the VR module for remote visualisations (Figure 6). The same VR environment can be used by operators for task planning, training and real operations. They can foresee difficulties before performing real operation, which primarily reduces heavy cognitive loads on the operators.

How can the operator remotely interact with the robot? Once the virtual environment is created and presented to the operator, they can interact with virtual objects within the environment. The object, which is to be handled/manipulated by the robot, can be indicated using a 3D selection technique that can either be 3D pointer based or 3D ray based. A 3D selection is broken down into various subtasks (object indication, selection confirmation and feedback) (Poupyrev and Ichikawa, 1999), allowing

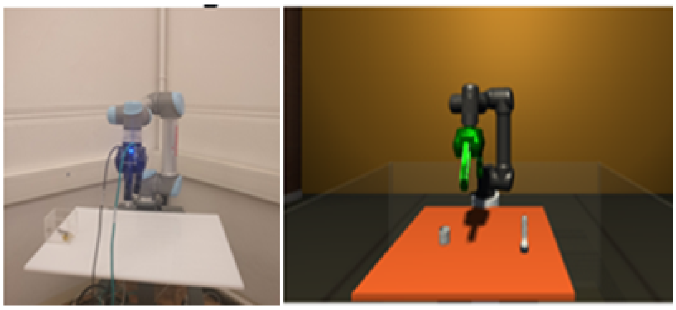

Fig. 6. Real and Virtual model

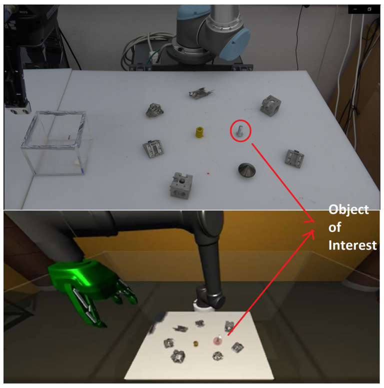

Fig. 7. Interaction with the environment in digital twin

the operator to quickly and precisely point at any 3D coordinates of the 3D virtual world (3D visualisation). In our system, a mouse pointer is used as a selection tool (Figure 7), and an onscreen visual feedback is provided to let the operator know that the intended selection is done.

After selecting the object of interest, the operator can send an instruction to the robot through a voice assistant or issue a command through console based GUI. The commands and operator's selection gestures within the virtual environment are interpreted to represent a goal and that representation is fed into decision manager (refer to section 2.5) of the robot to execute the necessary action.

5. CONCLUSIONS

Both a theory and a laboratory implementation has been presented for remotely instructed robots. The theory relied on formal description of an agent model and also included modalities of interaction with the operator. The novelty of RIRs is the balance they create in terms autonomy level in interactions with the operator. The robot is autonomous in task execution but it also aids the operator's ultimate decision making process on what to do next. Presentation of the robot's own model of the work scene enables corrections to be made by the robot, as well as it can enhance the operator's confidence in the robots work. RIR based glove boxes have been presented in technical details. Future work will focus on assessing operator experience with our system by industrial partners and use that information to make interface improvements.

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