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The effectiveness of virtual environments in developing collaborative strategies between industrial robots and humans

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Abstract

Testing and implementation of Human-Robot Collaboration (HRC) could be dangerous due to the high-speed movements and massive forces generated by industrial robots. Wherever humans and industrial robots share a common workplace, accidents are likely to happen and always unpredictable. This has hindered the development of human robot collaborative strategies as well as the ability of authorities to pass regulations on how humans and robots should work together in close proximities. This paper presents the use of a Virtual Reality digital twin of a physical layout as a mechanism to understand human reactions to both predictable and unpredictable robot motions. A set of established metrics as well as a newly developed Kinetic Energy Ratio metric are used to analyse human reactions and validate the effectiveness of the Virtual Reality environment. It is the aim that Virtual Reality digital twins could inform the safe implementation of Human-Robot Collaborative strategies in factories of the future.

Keywords: Reaction Metrics; Human Robot Collaboration; Virtual Reality; Digital Twin; Health & Safety Regulations; Manufacturing.

1.0 Introduction

The use of industrial robots in manufacturing and assembly lines is continuously increasing due to the need for high efficiencies, high accuracy, high production rates and repeatability. However, in some industries, the production line cannot rely on the use of robots only, and still require humans to perform some tasks that require creativity, adapting to unpredictable changes in the environment, fine motor skills and high dexterity such as cable assembly on a production line. As a result, interest and research in harnessing the natural and unique capabilities of both robot and human in collaboration tasks is increasing [1][2].

This has led to the development of collaborative robots such as Baxter [3], Sawyer [4], and the FANUC CR-4iA [5]. Nevertheless, in compliance to regulations, they move at a low speed in order to ensure that they do not cause damage when they collide with a human. They also have low payloads. This is because Human collaboration with an industrial robot could be dangerous due to the high-speed movements and massive forces generated by the robots.

Wherever human and industrial robots share a common workplace, accidents are likely and always unpredictable. As a result, in highly automated manufacturing systems industrial robots are located inside cages to constrain the physical interactions and proximities with humans. This leads to bigger size layouts, unused spaces and limited HRC operation. In order to avoid these drawbacks, the manufacturing sector is looking for new concepts beyond the current pre-defined safety measures to develop novel HRC strategies [1][2][6-10]. Novel HRC strategies that are currently being researched include turn-based strategies [8], automatic task allocation based on predefined metrics [10] and multi-modal communication with robots [2][7-9].

Nevertheless, the potential risk of injury to humans has reduced the progress of research in human robot collaborative strategies. This is because accidents could occur during the development of intelligent collaborative software and during the empirical experimental process of trial and error. Eliminating or reducing risks to humans during experiments could further aid the ability of authorities to pass regulations on how humans and robots should work together in close proximities.

A way to carry out this investigation is through Virtual Reality. The main idea behind Virtual Reality is the creation of a digital world in which a user can be immersed and interact with objects [11]. Although research in Virtual Reality has made significant progress in the last decades, the application within robotics is still in its infancy.

In manufacturing, Virtual Reality has started to be considered for several applications, such as programming [12][13], maintenance [14], process monitoring [15], product assembly [16], design and training [17] to mention a few. Virtual Reality provides a cost effective and safe environment to test various concepts and hypotheses before deployment in the real world. For example, Virtual Reality-based Training Systems (VRTSs) provide trainees with an environment to test and operate new equipment before it is installed. Important perceptual cues and multi-modal feedback (e.g., visual, auditory, and haptic) can be accessed in a Virtual Reality environment thereby enabling effective transfer of virtually acquired knowledge to real-world operation skills [18].

Virtual Reality also provides an opportunity to optimize factory layouts before construction [19-21]. In these cases, Virtual Reality has the potential to enable well designed layouts resulting in saving of up to 50% of operating costs. Optimization of manufacturing processes and tasks is another area that Virtual Reality lends massive benefits [22]. For example, complex tasks such as welding, drilling and screwing of parts require optimization of robot arm movement between different points in order to minimize span and maximize production rate. Achieving this via the programming of a robot arm is quite laborious and time consuming [12] [13]. Nevertheless, VR’s capability to represent virtual models of real world objects as well as present an intuitive programming interface makes it possible to simplify and speed up programming tasks. This also enables the generation of an optimization model that could be transferred onto a real world robot arm [12][23].

However, in order to achieve this seamless transfer, a digital twin of existing physical robotic cells is required. Development of digital twins requires a full synchronization between the real world at the shop-floor level and its digital twin. The synchronization enables a true reflection of the real factory and can be exploited to obtain current factory states as well as extrapolated to predict future factory states. It also opens up the possibility of experimenting with varying human presence sensing modalities in the robotic cell without comprising human safety [24].

According to regulations, human safety is achieved in HRC strategies by ensuring that collaborative robots do not exceed a certain size or exhibit certain speed profiles when interacting with a human. For example, the speed of a robot is reduced or stopped once a human is detected within a zone or minimum distance from the robot [23-28].

Other safety approaches being researched is through the modification of the robot’s current trajectory via collision risk informed control strategies. For example, in [29], the authors introduced a proactive control strategy based on risk analysis while in [30], the authors developed a Danger Index based on likelihood of an impact with a human. The danger index was increased when the human was facing away from the robot, because of the reduced likelihood of observing and being aware of the robot's motion.

Nevertheless, despite the control strategies discussed above, it has been shown that during a human-robot collaboration session, an operator's stress increases when the robot's speed increases; when the distance between human and robot decreases or when the operator does not know what the robot is going to do next [2][28]. This is partly due to the lack of awareness of the safety functionalities present on the robot as well as the lack of knowledge of safe working areas. New emerging technologies such as the use of augmented reality techniques that allow for the visualization of the robot operating and safe areas might alleviate this [31].

Another way to equip operators with knowledge of expected robot actions and an awareness of safety is through the use of Virtual Reality to construct a digital twin of the Human-Robot collaboration task. Virtual Reality also provides a safe environment to test and validate various Human-Robot collaborative strategies. However, what is the effectiveness of using such an environment considering that the participants would know it is a virtual environment?

Consequently, in this work, we investigate the effectiveness of using a virtual environment to develop Human-Robot collaboration strategies that involve proximate interactions on a task [7]. This involved developing a digital twin of a real physical layout of a manufacturing cell and then using a questionnaire to gather responds from participants regarding their experiences to various robot motions including unexpected ones. This enabled us to measure the effectiveness of using a virtual environment to represent a real manufacturing cell for human-robot collaboration sessions.

Furthermore, we developed and tested a set of new metrics (based on Kinetic energy as well as human direction of reaction) to gauge human reaction and behaviour to various robot motions in the virtual environment. The aim is that these metrics could be used to inform robot control strategies in the future. This is unlike the approaches used in [28-30].

The rest of this paper is organised as follows: In section 2, the methodology used in this paper is presented while in section 3, the experimental setup is discussed. This is followed in section 4 by experimental results while discussions are presented in section 5. Conclusion and future work is presented in section 6.

2.0 Methodology

In this section, we will discuss our experimental design. In order to use a Virtual Reality environment for accurately capturing and understanding human responses to robot actions, the realism of the virtual environment is essential. Furthermore, a mechanism to collect and analyse data is important. How these were achieved in this work are discussed in the next subsections.

2.1 Development of the Virtual Environment

The real world workshop consisted of a robot arm that can be programmed to carry out automated tasks of object placement, drilling, welding and visual observation of components. Currently, these tasks are done in a cage in order to separate humans and the robot arm.

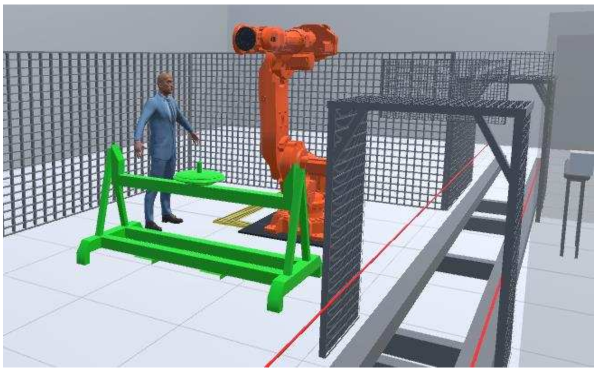
In order to create a digital twin of the workshop, physical measurements as well as photographs of real artefacts in a workshop were used to create corresponding CAD models

(Figure 1). The real-world robot is an ABB IRB 2600 12-1.85, whose predefined workspace is also depicted in Figure 1. The CAD models were transferred to Unity3D, a virtual gaming environment. The CAD models were placed in the virtual environment so that the physical dimension relationships between the objects in the workshop (real world) was respected in the virtual environment. This resulted in a 1-to-1 mapping of the real environment to the virtual environment.

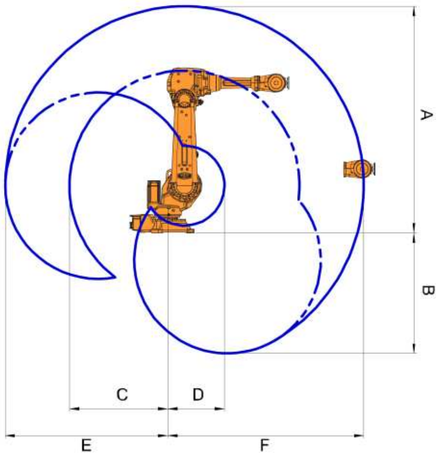
The virtual environment was experienced by the user via a HTC vive while interaction with elements in the environment was achieved through the use of hand controllers. This enabled the user to move freely in the 3D space of the real world as well as in the 3D space of the virtual environment (Figure 2).

The digital twin of the robot arm was capable of receiving coordinate data from the real robot arm on the factory floor. However, for investigating HRC strategies, the digital twin of the robot arm was programmed using the Denavit-Hatenberg method for forward kinematics.

(i) A real world workshop



(ii) Workshop environment replicated in Unity. The human manikin is used as a visual aid to understand the reaction of users during playbacks.



Pos. A	2148mm
Pos. B	1174mm
Pos. C	967mm
Pos. D	506mm
Pos. E	1553mm
Pos. F	1853mm

(iii) The working space of IRB 2600 12-1.85 [32]

Figure 1. A digital twin of a physical workshop.

In order to measure human reaction during experiments, two classes of robot arm trajectory were programmed. The first class of trajectory was smooth and predictable. The robot was programmed to use this trajectory at the beginning of an experiment. The experiment consisted of the transportation of boxes from one location to another. In order to make the user experience a HRC session, the robot waits until it is fed with a box by the human. When fed, the robot arm moves and places the box at a predefined place in the Virtual environment. After dropping the box, it goes back to the place where the user is located and waits for the next box. This loop is repeated about 4 times in order to draw the user into the experience and build user confidence (Figure 2).

Then, the robot arm performs the second class of trajectory which consists of an unpredictable and dangerous movement that attacks the user and moves against the user's forehead. During these two classes of robot trajectory, we collect the data of the user's reaction to the robot arm.

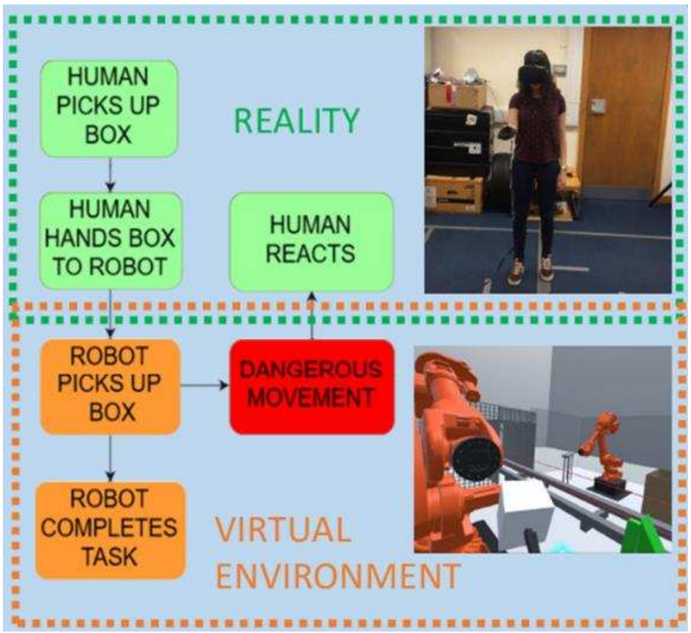


Figure 2. Human-Robot task setup and human interaction with the virtual environment

2.2 Data collection and data analysis

Data is collected using a Kinect motion capture system. It enables data of the kinematics of the human reaction with respect to the robot arm kinematics to be captured in real time. The robot arm kinematic data was obtained from the Virtual Reality environment.

The Kinect motion capture system streams joint co-ordinates in X, Y, Z. From this data stream, it was possible to derive Acceleration, Kinetic Energy, leaning angle, movement direction and force related danger metrics as shown in Figure 3 below. The importance of these metrics shall now be explained as follows.

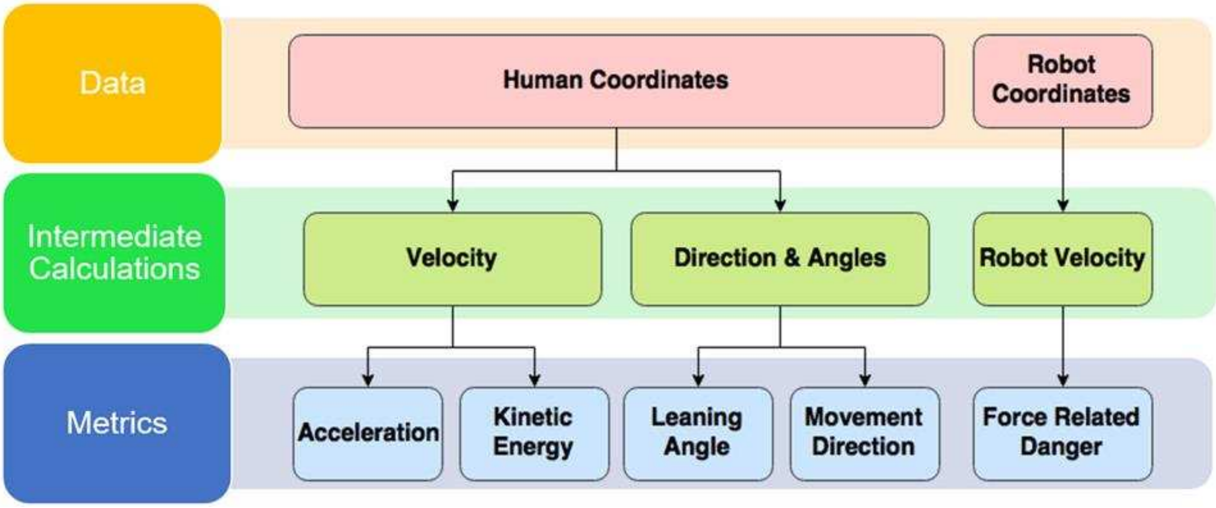


Figure 3. Relations between collected data and human reaction metrics. Robot coordinates were obtained from the Virtual Reality environment

2.2.1 Acceleration: was used to evaluate human reaction over a period of time. Acceleration is widely used in literature for characterising human reactions, making it a reliable metric [33].

It is given by the equation:

$$a = \frac{v(t_2) - v(t_1)}{(t_2 - t_1)} \tag{1}$$

With the velocity being the average velocity over a period of time given by:

$$v(t_2) = \frac{d(t_1, t_2)}{(t_2 - t_1)} \tag{2}$$

With $d(t_1, t_2)$ being the distance covered between t_1 and t_2. The acceleration is calculated for every joint in each time interval(t_1, t_2) .

2.2.2 Kinetic Energy Ratio: This method is introduced in this paper and consists of calculating the ratio of the human Kinetic Energy (KE) spent per unit time during the robot's jerky period and during the robot's smooth period.

$$r_{KE} = \frac{KE_2 / \Delta t_2}{KE_1 / \Delta t_1} \tag{3}$$

KE_1 is the KE spent by the human during the first phase (the duration of this phase is Δt_1), normal behaviour of the robot, and KE_2 is during the second phase (the duration of this phase is Δt_2), during which the robot will be carrying out a dangerous motion.

The total Kinetic Energy spent during each phase is calculated with the formula:

$$KE_i = \sum_{\Delta t_i} \frac{1}{2} m v^2 \tag{4}$$

It is the sum of the Kinetic Energy spent between each measure. Since every participant has a different behaviour and spends different amount of Kinetic Energy to perform the same tasks, the ratio was proposed to reduce the effect of this variation from one participant to another.

In order to calculate the Kinetic Energy with accuracy, it is necessary to have an accurate body model. [34] states that the body segment can be divided in four groups according to their weight as shown in Table 1. As a result, each joint recognised by Kinect was designated to its corresponding group as shown in Table 2.

The geometrical centre of each body segment was calculated and the percentage of the body mass was calculated for each centre thereby making the calculation of the Kinetic Energy more accurate. The final Kinetic Energy is obtained by summing the Kinetic Energy spent by each segment during the experiment. The use of Kinetic Energy to calculate human reaction is according to our knowledge, a newly defined metric to assess human reaction.

Categories	Weight Percentage
Head and Neck	6.81%
Trunk	43.02%
Arms	9.43%
Legs	40.74%

Table 1. Body Segment Data [30].

Categories	Joints included
Head and Neck	Head, Neck
Trunk	Right Shoulder, Left Shoulder, Spine Shoulder, Spine Mid, Spine Base, Right Hip, Left Hip
Arms	Elbow, Wrist, Hand, Hand Tip, Thumb
Legs	Knee, Ankle, Foot

Table 2. Designation of joints to body segments

2.2.3 Direction of reaction: In this work, this metric was developed and investigated because an effective collaborative strategy for human-robot safe collaboration is closely linked with the direction of human reaction. The direction of human reaction will help inform the direction of movement the robot should adopt. It will also provide information as to the reaction of the human during various behaviours of the robot.

A base coordinate system between the human and robot was defined in the immersive environment (Figure 4). For convenience, the virtual robot's base coordinate system serves as the basis for Kinect sensor's coordinate system, whereby the real-world Kinect location is placed where the base of the virtual robot would be. Note that two corrections are necessary:

1. The raw x,y,z coordinate data from Kinect must be transformed from Kinect's coordinate system into the base coordinate system. Thanks to co-location of Kinect

with the virtual robot's base coordinate system, this transformation is simple: $(X, Y, Z)_{corrected} = (Z, X, Y)_{Kinect}$.

2. Kinect is ideally placed at a height of 1.5m, therefore a correction of

   $Z_{base} = Z_{corrected} - 1.5m$

   is necessary.

The base coordinate system enabled the direction of human reaction to be defined using a factor called "angle of lean." The angle of lean, 'α', is the angle between the neutral position of the human (when standing still and straight) and the position in response to the robot's actions in real time.

By assuming that the spine base joint and head joint were a single straight line, and using the position of the spine base joint as the origin, α could be determined for each time interval (Figure 5).

In Figure 5, α_y is the angle of bend in $\mp$ y direction i.e. either towards the robot (-) or away from the robot (+) direction from the initial mean position while α_x is the angle of bend in $\mp$ x direction i.e. either left (+) or right (-) direction from the initial position. The angle of lean provides precise information regarding the bending of human at the waist along the Y axis such that if $\alpha_y < 0$ then there is a lean towards the robotic arm and if $\alpha_y > 0$, there is a lean away from the robotic arm. Similarly, along the X axis, if $\alpha_x < 0$, then the human is bending right side from the neutral position while if $\alpha_x > 0$, the human is bending to the left side from the neutral position. These data could be used to give a clear feedback to the robot manipulator to control its path in order to avoid collision/accidents.

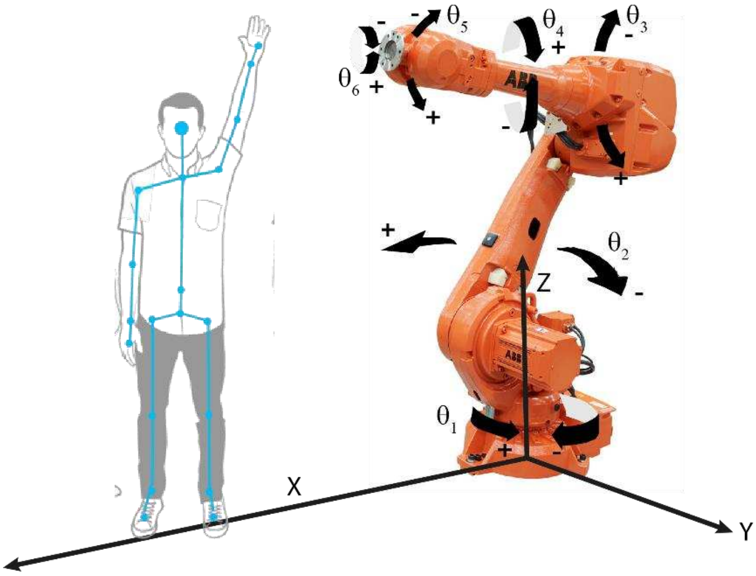


Figure 4. Base coordinate system of the immersive environment along with robot rotation angles.

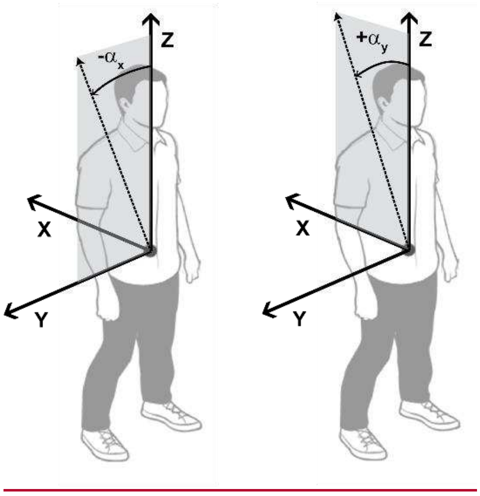


Figure 5. Angle of lean α calculation. Left: Angle of bend of human reaction in x axis, (ii) angle of bend of human reaction in y axis.

2.2.4 HIC-based Force Related Danger: This metric was used to calculate the effect on the human if a robot were to hit the human. An HIC (Head Injury Criteria) equation was defined by [35] as Equation 5.

$$HIC = \Delta t \left(\frac{1}{g\Delta t} \int_{t_2}^{t_1} a \, dt \right)^{2.5} \tag{5}$$

$$with \;\; \Delta t = t_2 - t_1$$

Where t_1 and t_2 are any two points in time during the collision which are chosen to maximize the HIC with the condition that Δt must be less than 15 millisecond (ms) to be relevant to head concussion and a is the resultant acceleration after the collision at the centre of gravity of the head.

Calculated HIC values are translated to a “probability of sustaining an injury of a certain level”. Those levels, are usually expressed by the Abbreviated Injury Scale (AIS). The reader may refer to [35] for more information.

Using an acceleration equation obtained from the mass-spring-mass model and the HIC formula (5), an HIC-based acceleration can deduced and is defined by [31]:

$$a(HIC) = \frac{2v_0 \frac{M}{m} \sqrt{\frac{M}{m+M}}}{\Delta t} \tag{6}$$

Where v_0 is the approach velocity; Δt is the duration of the impact; M is the robot arm effective mass and m is the human head mass (4-5kg). Using Newton’s second law, the HIC-based force applied to the human by the robot arm can be deduced as Equation 7.

$$F = m * a(HIC) = \frac{2v_0 M \sqrt{\frac{M}{m+M}}}{\Delta t} \tag{7}$$

Once calculated, this force could be compared to critical forces, such as fracture critical forces or pain tolerances. However, there are some limitations to this criterion which are related to the HIC limitations: (1) It is only suitable for frontal and blunt impacts; (2) The approaching speed of the robot is supposed to be uniform and the human is supposed to be at rest, whereas they are not in our experiments (3) the stiffness of the robot and the head is not represented whereas it should a determinant factor and finally, this criterion only applies to the head and as such, it is not suitable for other body parts.

3.0 Experiment setup

The experimental setup comprised of an immersion of human participants in a virtual environment and performing HRC tasks. As mentioned before, the interaction between the human and the virtual robot was established by repeatedly feeding the robot's end effector with a virtual box. The robot moves with a pre-defined trajectory following a pick/drop mechanism. The coordinate data (x, y, z) and rotation data (α, β, γ) of robot kinematics were collected and time-stamped along with the human skeleton joint and rotation data.

Two classes of experiments were carried out with 53 individuals between the ages of 21 to 25 years old and with mixed gender participating. This two stage approach was necessary because we did not want to carry out the second class of experiments without ensuring that the environment exhibited a level of realism to achieve user immersion. This ensured that we could get more realistic human reaction data as we might have, if the human was collaborating with a real robot. For both classes of experiments, the setup discussed in section 2.1 and shown in Figure 2 was used.

The first class of experiments: was made up of 22 randomly selected individuals and the experiment was used to gauge the realism of the Virtual Environment before conducting the next class of experiment. In this experiment, the robot arm was programmed to perform the two classes of trajectory discussed in section 2.1. In order to capture participant's responses to the robot actions, a questionnaire was designed for the participants to fill out. The participants were asked about previous experiences with VR and industrial robots, as this could be relevant in understanding their perception of the realism exhibited by the created virtual environment. They were also asked if they would have reacted in the same way to a real robot and what their overall experience with the virtual environment was like (Please see Table 3 for more information).

The second class of experiments: was made up of 31 randomly selected participants and the experiment was used to collect data on how participants reacted to the two robot motion trajectories. The collected human reaction data was then analysed using the proposed metrics in section 2.2.

It is necessary to understand the link between the proposed metrics and the collected data. The developed system extracts 7 different components of the 25 joints composing the tracked body: 3 coordinates and 4 orientations components. At the same time, a script was embedded in Unity to record components of the 6 joints comprising the end effector of the collaborative robot: 3 coordinates and 3 rotations angles around the three axes. It means that every frame, the system records 175 values for the human body and 18 values for the collaborative robot (An ABB robot arm). Since our frame rate is approximately 50 frame per second (fps), the system records more than 10,000 values per second.

The above data was stored in a .csv file. In the second class of experiments, these data were used to develop a replay feature that was used to playback the collected data of the 31 participants. Due to the 1-to-1 mapping between the real and virtual world (as discussed in section 2.1), a 3 dimensional play back of experiments was achievable in the virtual environment. As a result, this enabled us to analysis the collected data more closely.

The playback feature revealed that the data of 9 participants were not suitable for further analysis and therefore had to be discarded from processing (e.g. the participant did not complete the full experiment or the Kinect tracked someone else in the room).

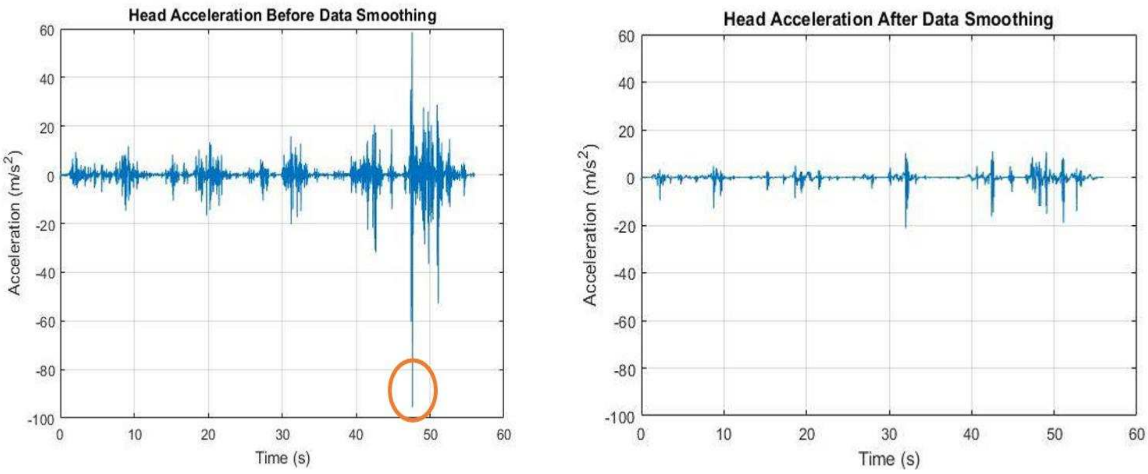
Furthermore, the collected data was analysed offline using a developed MATLAB script. Offline analysis was essential due to the large amount of data generated during each experiment.

Sensor noise from the Kinect was an issue in our experiments. In order to reduce noise, data smoothing was carried out using the Savitzky–Golay filtering method. “The Savitzky-Golay smoothing and differentiation filter optimally fits a set of data points to a polynomial in the least-square sense” [36]. This method was very effective in eliminating noisy peaks in the data set.

For example in Figure 6, the acceleration of the head reached a value of approximately -90m/s^2. This data point was not realistic for a human’s head. However, after smoothing, the values lied in a reasonable gap. It was then possible to proceed with further analysis.

The Figure 7 displays the KE spent by the Head and Neck segment during the duration of the experiment, along with the robot’s end effector z-coordinate (useful to identify the smooth and jerky periods of the robot). It is noticeable that the KE’s peaks correspond to the moments when the robot’s arm approached the participant. Furthermore, a survey was conducted among all participants after the experiments to obtain feedback.

The Virtual Reality environment was developed on a computer with the following specs: 16GB RAM, an Intel(R) Core(TM) i7-4790K CPU @ 4.00GHz (8 CPUs) and a GeForce GTX 980 Ti graphics card. Microsoft Kinect V2 was used for motion capture.



(i) Acceleration values obtained from raw data

(ii) Acceleration values after smoothening

Figure 6. Head acceleration before and after smoothing.

4.0 Results

This section discusses the results obtained using the proposed metrics presented in section 2.2. As an example of what analysis was carried out on the data sets collected from the 22 participants, this section focuses on one of the data sets collected from an individual.

4.1 Kinetic Energy Metric: Figure 7 below displays the Kinetic Energy of the Head and Neck segment during the duration of an experiment, along with the robot's end effector z-coordinate (useful to identify the smooth and jerky periods of the robot). It can be noted that their Kinetic Energy peaks when the robot's arm approached the human to be fed with the box. This can be observed at 10, 20, 30 and 40 seconds.

In between these intervals of time, the Kinetic Energy of the head of the participant drops almost to zero while waiting for the robot to complete the task. At around 50 seconds, the density of the Kinetic Energy is much higher than at the previous times. This is because of the jerky movement of the robot identified by the sudden irregular trajectory of the z-coordinate of the end effector.

4.2 Acceleration: The second metric to consider was the acceleration of the human's head. As mentioned before, the calculation of the acceleration has been widely used for the characterisation of human reaction. The head was chosen among all the joints as the most representative one to quantify the human reaction. After data smoothening as described in section 3, the average acceleration was calculated.

Figure 8 shows the acceleration of the head joint during the whole duration of the experiment. It also shows how it changes with the movement of the robot's end effector. The highest density periods on the graph correspond to the times when the robot's arm approaches the human to be fed with the box. Finally, the highest density and peak period is directly related to the jerky movement of the robot. This correlates with the Kinect Energy graph in Figure 7.

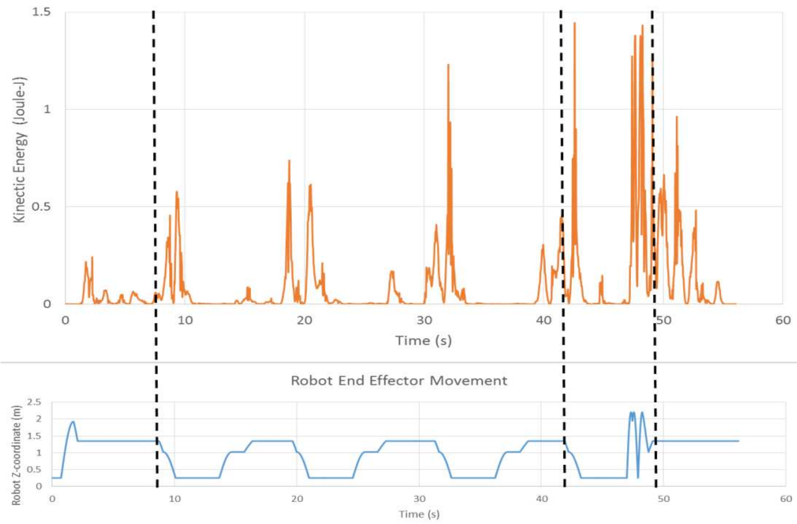


Figure 7. Kinetic Energy of the head and neck segment (Orange curve) and the Robot arm end effector (Blue curve) during the experiments.

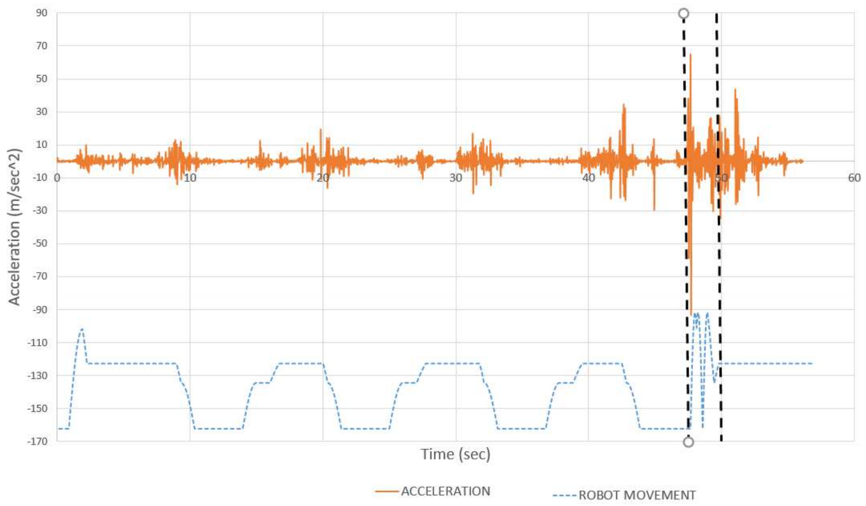


Figure 8. Head acceleration during the experiment. The head acceleration increased during jerky robot arm movement.

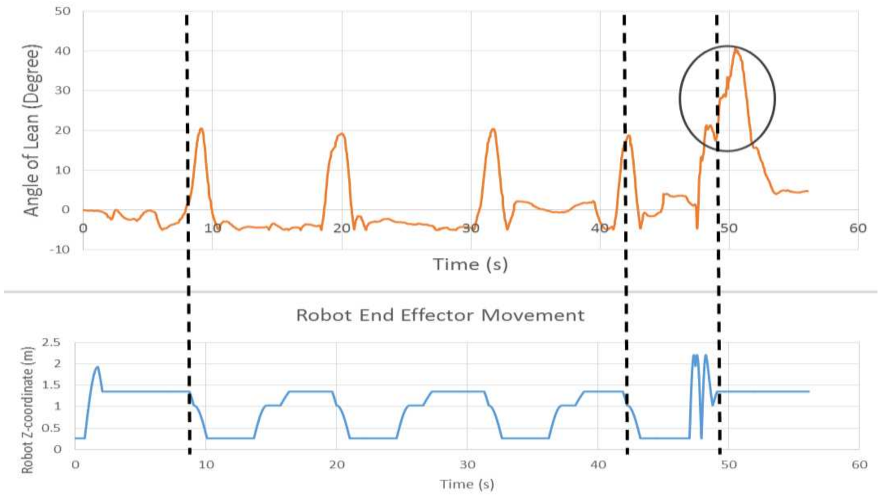


Figure 9. The angle of lean during the experiments. α < 0 : human towards the robot. α > 0 : human away from the robot. During the jerky motion of the robot arm, the angle of lean increases.

4.3 Direction and Angle of Reaction: Figure 9 shows the variations in the angle of lean during the duration of the whole experiment. As mentioned before, when the lean angle is positive, it means that the human is bending away from the robot, while a negative value represents a movement towards the robot. It can be observed that when a participant was feeding the robot, the angle of lean was a negative value.

After the feeding phase, the angle increases because the participant steps backward to grab another box. Noticeably, during the jerky period, the angle increases rapidly and reaches a peak of 40° degrees that represents a significant inclination of the human's head away from direction of the robot. This shows that the human reacted in accordance to the sudden robot movement.

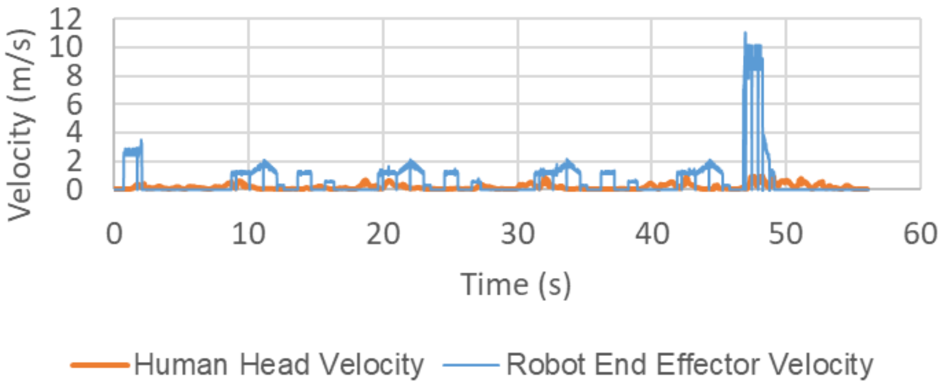


Figure 10. Human vs robot velocities during the experiments

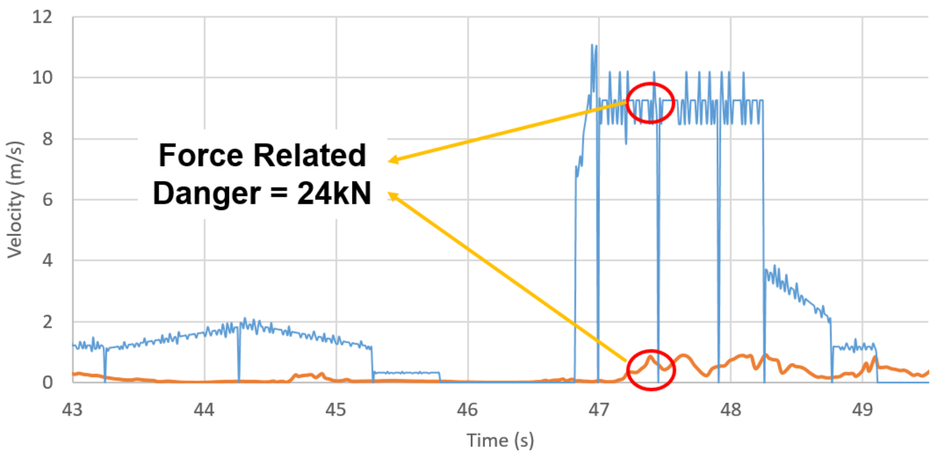


Figure 11. Calculated force related danger using Equation 7.

4.4 HIC-based Force Related Danger: Figure 10 displays the velocity of the human's head and the robot arm's end-effector during an experiment. The robot has been intentionally programmed to have a fast speed during its jerky motion period.

An amplification of the previous graph in Figure 10 is shown in Figure 11, where the difference between human and robot velocities is shown more clearly. Using the obtained data and Equation 7, it was possible to calculate the hypothetical force that would have been applied by the robot's arm to the human's head if a collision were to happen in a real world scenario. A force of 24KN was generated by the robot arm and this could have resulted in the death of a human participant.

5.0 Discussion

This research was started out with the need to investigate whether virtual reality environments could provide a safe and effective environment to carry out human-robot collaboration research. Towards this end, a digital twin of a real world workshop was constructed in a virtual environment as well as a motion capture system used to collect human skeletal data from participants. The collected data were then passed through both established and newly developed metrics in order to judge human reactions to various robot motions including motions that were unexpected, jerky and potentially fatal. The goal is that the environment could be used to collect data from human participants to inform robot motions in the future. This should potentially result in new, informed and safe human-robot collaboration strategies.

5.1 Analysis of realism of the developed Virtual Environment: A survey was carried out among participants using the Virtual Environment. Data from 22 participants were collected in this experiment. As seen in Table 3, the participants were made up of 8 people with no previous virtual reality experience, 14 people with previous virtual reality experience, 6 people with experience of industrial robots (meaning that they use industrial robots most days in their work) and 16 people with no experience of industrial robots.

The data in the questionnaire was processed by scoring the reaction and attitude of the participants to the robot motion in the virtual environment.

In scoring reaction in this context, we were measuring if they would have reacted to the robot as they would have in the real world or not. Figure 12 shows that people with or with no VR experience reacted to the robot with the same amount of magnitude.

Figure 13 also shows that people with real robot experience did not react as much as those that did not have real robot experience.

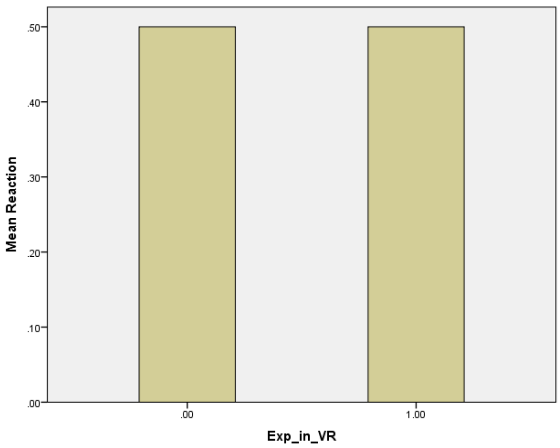


Figure 12. Showing the mean of reaction responses vs experience with VR. .00 is code for No experience with VR while 1.00 is code for Yes.

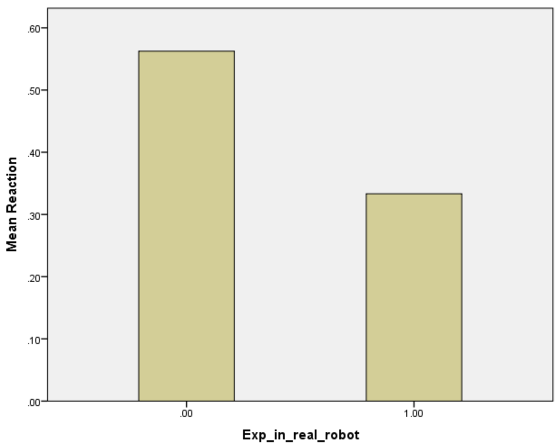


Figure 13. Showing the mean of reaction responses vs experience with real robot. .00 is code for No experience with a real robot while 1.00 is code for Yes.

However, if we look at participants 3 and 5’s response, it seems that their No response is actually a Yes response. For example participant 3 commented*: “Nope, I think I would ha*ve *step back.. If I would have time”* meaning that Yes, he/she would have reacted if they had the time to move out of the way of the robot. Participant 5 also commented: *“I think I would* move out of its way quicker - *but I canot be sure”* seeming to suggest that he/she would have reacted as well and moved out of the way of the robot.

But perhaps because of their experience with industrial robots they knew they would not have had enough time to react if it was a real robot. By looking at these comments and those of others with industrial robot experience, it shows that the VR environment has the potential to be representative of the actual environment in which the industrial robot arm operates.

	Have you use VR before?		Have you seen and work with real life robot?		How was your experience?	Do you think you would have react the same had it been a real robot ?	
	Yes	No	Yes	No		Yes	No
Participant 1	x			x	Awesome		No
Participant 2	x			x	Did not expect movement so fast, a bit scaring	Yes, Approximately the same	
Participant 3	x		x		Funny, alsways great to use virtual reality. Nice quality, feels almost real		Nope, I think I would have step back.. If I would have time
Participant 4		x		x	Excellent, but the software was lagging slightly	Yes,	
Participant 5	x		x		Clear tasks to perform Robot would kill me! There was no warning sign for me that the robot is going to hit me Safety space would help – if i knew how far from it I need to be to avoid physical contact		I think I would move out of its way quicker – but I canot be sure
Participant 6	x			x	Easy task to perform, suprised by the unexpected behaviour		maybe i will have moved quicker
Participant 7		x		x	Great but looked like the vision is filtered (image accurancy)		No
Participant 8	x			x	Good, the robot is realistic and the vision is good (sometimes the image makes me feel deasy but here it was good)		I think I would react faster with a real robot because I knew that is was a VR
Participant 9		x		x	It seemed really realistic, easy to use, quite simple as the task was well explained	I think similarly as I took a step back when the robot seemed to launch at me.It did seem very realistic	
Participant 10		x		x	It was interesting because I've never tried it before.	Yes but at the end it did a strange movement and I'd have move away	
Participant 11	x		x		Good to check dangerous behaviour of machines		No
Participant 12	x			x	i was suprised by the robots behaviour	Yes	
Participant 13		x		x	Fun, exciting, a bit scary		No
Participant 14	x		x		great because It was like been in a real factory	yes	
Participant 15		x		x	It seems really realistic		I would be more focused in reality
Participant 16	x			x	It was interesting to simulate this situation and makes me want to do it in a real-life situation	Yes	
Participant 17		x		x	It was a good exprience knowing that we can stimulate the real life scenarios using the VR. All the cases of simulations can be run in a safe environment with affecting the real productivity and work.	Yes	
Participant 18	x			x	Funny, good	yes	
Participant 19	x		x		Sudden , quick, virtually dangerous	yes	
Participant 20	x			x	Realistic	Yes	
Participant 21	x		x		Funny, good		No
Participant 22		x		x	Awesome to see VR working in real live		No
Total	**14**	**8**	**6**	**16**		**11**	**11**

Table 3. Results of survey carried out among participants

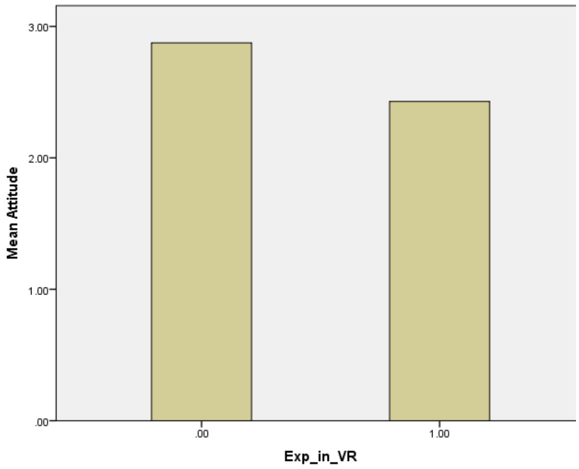


Figure 14. Showing the mean of attitude responses vs Experience in VR. .00 is code for No experience in VR while 1.00 is code for Yes.

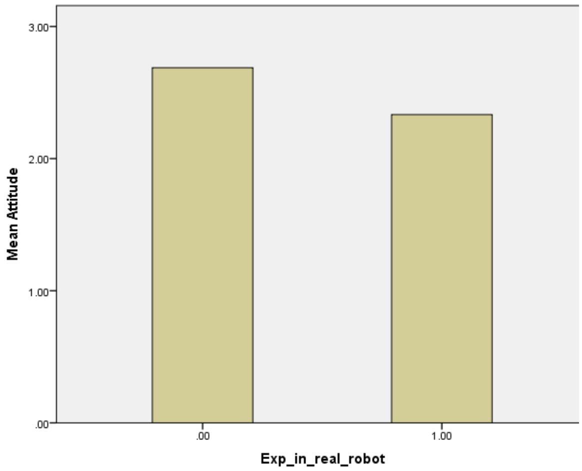


Figure 15. Showing the mean of attitude responses vs Experience with working with Robots or as seen a working robot in operation. .00 is code for No experience with a Robot while 1.00 is code for Yes.

	VR Experience		Industrial Robot Experience		Final KE Ratio	Reaction	Accordance with Observation
	Yes	No	Yes	No			
Participant 1		x		x	0.908184149	Low	Yes
Participant 2	x			x	1.491934	Low	No
Participant 3	x			x	2.812031	High	Yes
Participant 4		x		x	3.085502	High	Yes
Participant 5	x			x	1.769956	Low	No
Participant 6	x		x		0.189137	Low	Yes
Participant 7		x		x	0.454912	Low	Yes
Participant 8		x		x	2.421551	Medium	Yes
Participant 9	x			x	0.469138	Low	Yes
Participant 10	x			x	3.858684	Medium	No
Participant 11		x		x	0.68106	Low	Yes
Participant 12		x		x	1.087817	Medium	No
Participant 13	x			x	1.186584	High	No
Participant 14		x		x	1.073079	Low	Yes
Participant 15	x			x	0.641418	Low	Yes
Participant 16	x			x	0.873797	Low	Yes
Participant 17		x		x	0.208117	Low	Yes
Participant 18		x	x		0.04566	Low	Yes
Participant 19	x			x	0.957383	Low	Yes
Participant 20	x			x	3.300583	High	Yes
Participant 21	x			x	0.083438	Low	Yes
Participant 22		x		x	0.708075	Medium	No
Total	**12**	**10**	**2**	**20**			

Table 4. Showing Kinetic Energy ratio and previous experience of Virtual Reality. *black: ratios are in accordance with the observed reaction. red: values not in accordance with the observed reaction.

After removing the red values, the median Kinetic Energy ratio of participants with no previous Virtual

Reality experience was 0.7946 compared to the median Kinetic Energy ratio of 0.7576 with previous Virtual Reality experience.

In scoring attitude, a scale of 1 to 3 was used. The participants that gave a negative attitude of the robot due to its sudden movements and speed were given a lower score. For example, comments like “Sudden, quick, virtually dangerous” received 1 while comments like “Fun, exciting, a bit scary” received a score of 2. Figures 14 and 15 show that people with previous experience of VR or having seen as well as worked with Robots were able to see perceive the danger of the sudden robot movement in the VR environment and as a result, had a negative attitude. Both analysis of attitude and reaction feedback from the participants’ shows that the virtual environment could be sufficient to act as a substitute for collecting data about human reactions to unexpected robot movements.

5.2 Analysis of human reactions to robot movements using the proposed metrics of Kinect Energy Ratio: 31 participants were used in this set of experiments. But 9 were rejected due to issues such as the participant not completing the full experiment or the Kinect tracking someone else in the room. 12 people had no previous virtual reality experience, 10 people with previous virtual reality experience, 2 people with experience of industrial robots and 20 people with no experience of industrial robots (Table 4).

Analysis of the data showed that the 22 participants could be classified into three groups according to a visual observed reaction: low, medium and high reaction (Figure 16). Visual observation of participant’s reactions were classification by:

- Observing the overall reaction of the participant
- Observing by how much the participant shifted from the neutral position
- Observing the movement speed of the participant during the robot arm feeding process
- Observing the reaction magnitude of the participant during robot arm jerky motions

The participants in the low reaction group did not show any reaction or very low reaction. This meant that the participants’ movements did not shift or slightly shifted from the neutral position throughout the experiment. The participants in the medium reaction group reacted to dangerous movement of the robot by leaning the trunk slightly backwards or taking a small step back from the robot. The participants in the high reaction group showed the highest movement’s speed and the magnitude of their reaction was higher than the other two groups during the jerky phase of the robot. These participants expressed their reaction by taking large step backward or jumping back away from the robot.

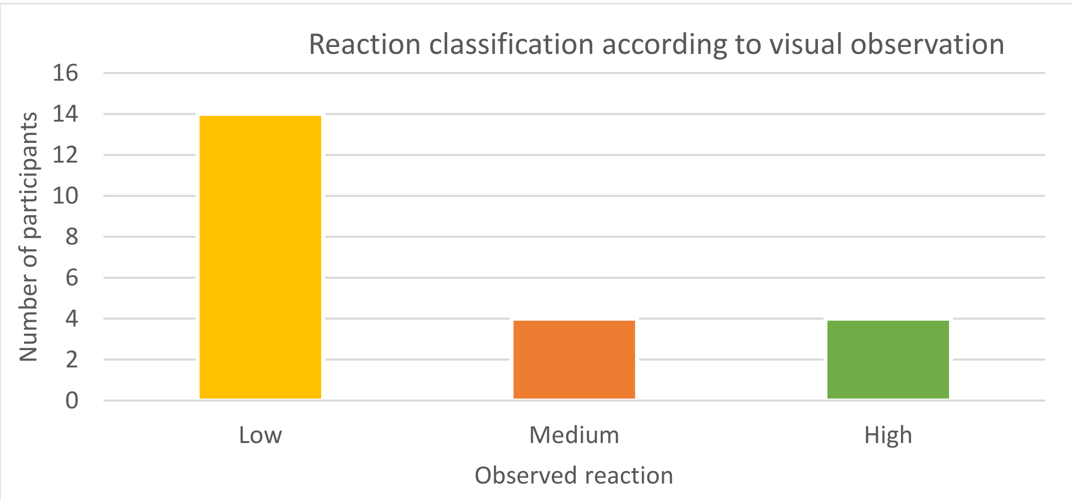


Figure 16. Classification of participants Kinetic Energy ratio according to their reaction to unexpected jerky motion of the robot arm.

As seen in Figure 16, there was a high frequency of low reactions among the participants. These visual observations were compared with the Kinetic Energy ratio metric discussed in Section 2.2.

The calculated Kinetic Energy ratio was classified using values as follows: An analytical Kinetic Energy ratio < 1.10 was deemed to belong the low reaction group: 1.10 < KE < 2.40 belonged to the medium reaction group and 2.40 < KE < 3.30 was deemed to belong to the high reaction group. Table 5 below presents the comparison of the Kinetic Energy ratio metric analysis with the visual observed reactions.

Observed reaction	**Low**		**Medium**	**High**
KE Ratio	0.04566	0.68106	0.70808	1.18658
	0.08344	0.87380	1.08782	2.81203
	0.18914	0.90818	2.42155	3.08550
	0.20812	0.95738	3.85868	3.30058
	0.45491	1.07308		
	0.46914	1.49193		
	0.64142	1.76996		

Table 5. The Kinetic Energy (KE) ratios for each participant sorted according to the observed reaction of the human. Analytical KE ratio < 1.10 should belong to low reaction, 1.10 < KE < 2.40 should belong to medium and 2.40 < KE < 3.30 should belong to high reaction. *black: ratios are in accordance with the observed reaction. Red: values not in accordance with the observed reaction.

In the low reaction group, it was revealed that two analytical ratios were not matching with the visually observed reaction because they were too high. In the medium reaction group, 3 ratios were not satisfactory; either too low or too high, and in the high reaction group, one ratio was too low.

Thus, over 22 participants, the analytical results of 16 (73%) were in accordance with the observed reaction, which means that a person with high reaction in the reality, has also high analytical Kinect energy ratio, and the same applied for participants with low and medium reactions.

However, 6 out of 22 participants' ratios (27%) did not match with the observed reactions, but this incoherence could be justified by in depth analysis of the data along with the playback feature.

For example, a person who had a high magnitude of reaction during the jerky phase of the robot but moved more than usual during the smooth robot phase could show a low Kinetic Energy ratio. It is also possible to explain the results obtained for participants who were classified according to observation into the low and medium reaction groups but who have a high overall Kinetic Energy ratio. For example, a person who slightly shifted the position in the jerky movement of the robot ended up to belong to the high reaction group because during the smooth phase he moved in a stable manner or without shifting from the origin position. Thus, for this scenario, the movement showed in unexpected robot situation was greater than the one during the normal period of the robot, with the consequence of having a high overall KE ratio. However, by analysing the replay session of their experiment, the participants showed either no reaction or slight reaction. Therefore, they cannot be really categorised in medium or high reaction group even they have overall high kinetic ratios.

During the assessment of the Kinetic Energy ratio metric, it was recognised that the behaviour of the person during both the smooth and jerky periods play an important role in determining the individual Kinetic Energy ratio. Though, this metric is a new innovative metric to quantify human reaction, it was demonstrated that it could accurately classify 73% of the analytical data according to the observed reaction. Nevertheless, there is still room for the experiment to be conducted on more diverse data such as different age group, academic backgrounds or industrial experiences. More data would provide more evidence, which would lead to a refinement of the developed metric for greater reliability and accuracy in classifying human behaviour.

As seen in Figures 7, 8 and 9, the Kinetic Energy ratio correlates with other metrics such as acceleration and angle of lean metrics. Together they could be used to inform robot control strategies during human robot collaboration sessions. Furthermore, the HIC-based force related danger index could be used to safely measure collision effects during human-robot collaboration session without the risk of injury to humans. This index could be used for gamification training sessions.

5.3 Possible correlation between human reaction and previous experience of Virtual reality: An analysis was conducted in order to ascertain if there was a relationship between human reaction and personal characteristics such as previous experience of virtual reality.

It was discovered that it was possible to identify a correlation between people's characteristics and reactions observed; for instance, participants with previous experience in virtual reality were more used to the unreal environment. Thus, even when the robot approached them at high speed they were aware that it was not a risky situation. They stated that they did not feel completely immersed in the developed virtual environment because of the lack of audio and physical feedbacks such as vibration in controller when robot was colliding with them. As a result, they exhibited a low reaction to the jerky motion of the robot arm.

Some participants who were experiencing the virtual reality for the first time did not show a relevant reaction as they were distracted by the virtual environment and did not notice when the robot started to initiate the dangerous movement. However, the median of the Kinetic Energy of this group was higher than the group with previous experience of a virtual reality environment (Table 4). This could be explained by the fact that people with no previous experience had to go through a "learning stage" at the beginning of the experiment making their movement less accurate and, thus increasing their overall KE.

Initially, it was thought that people with previous experience of industrial robots will be more aware of the danger and react accordingly. However, their reaction was actually low and they ended up belonging to the low-reaction group. Nevertheless, as discussed in Section 5.2, this could be because they knew they would not have had enough time to react if it was a real robot.

6.0 Conclusion

In this work, an investigation into the effectiveness of using a virtual reality (VR) environment to inform the development of human-robot collaboration strategies was carried out. This investigation is particularly important because such a virtual reality environment presents a low cost solution to Academia and SMEs interested in experimenting and developing strategies for collaborative robotics.

For SMEs, such an environment enables them to test if the potential human-robot collaborative strategies they are considering will work without the need to buy expensive equipment. In some cases, having a low cost solution to test their strategies could be the difference between developing a product that nobody wants and developing a product that is useful. By using such an environment developed in this paper, they can at least get a first set of results from potential users of their system before going full scale. For Academia, it presents a good environment in which low technology readiness level algorithms and approaches can be trialled, analysed and presented to the wider community.

Towards achieving the above, a survey was used to collect participants' attitudes to the developed VR environment. The survey also collected participants' reactions to unexpected robot motions. It was discovered that if a virtual environment is designed and developed well, the realism offered by it could be effective in understanding human reactions to both expected and unexpected robot actions (Section 5.1).

Quantitatively, human reactions were quantified using a set of metrics comprised of acceleration, Kinetic Energy ratio, leaning angle and force related danger. The acceleration metric is a metric commonly used in literature while the leaning angle and Kinetic Energy ratio metric were newly developed in this work. The Kinetic Energy ratio metric enabled us to derive an overall measure of the human-robot collaboration experience of a participant.

The Kinetic Energy metric enabled us to classify people into one of three groups: low, medium and high reaction groups (Section 5.2). It was discovered that there might be a correlation between their reaction to the robot arm and previous experience of virtual reality. A correlation between their reaction to the robot arm and previous industrial experience with robots still needs to be ascertained (Section 5.3).

Using visually observed behaviour as a benchmark, the Kinetic Energy metric was able to accurately classify participants up to 73%. In future work, more data will be collected to refine this metric. This will comprise participants from a broaden age range, background and industrial experiences.

Nevertheless, in section 4, it was shown that the newly developed Kinetic Energy metric correlated with the acceleration metric as well as the leaning angle metric. The newly developed leaning angle metric enabled us to derive a measure of how far the human leaned away from the robot during unexpected motions as well as in what direction. This information could be used to control a robot's motion in the future.

Finally, the HIC-based force related danger metric enabled us to measure the force that would have been applied to a human if a robot had collided with him or her. We believe that this metric will be useful in gamification of the virtual environment tool as well as aid authorities in passing regulations in respect to human-robot collaboration strategies in industry.

In future work, we plan to expand the capability of our Virtual Reality Environment by considering highly skilled manufacturing tasks in various sectors. One immediate task is composite manufacturing in the aerospace sector. For example, there is active research in improving current manual composite layup through human-robot collaboration. A robot "third hand" that can manipulate material with full awareness of the position of human limbs can help increase productivity, e.g. by picking up and correctly positioning the next fibre work piece; by fixing the composite fibre against the mould so that a human operator can shear the material with both hands; or many other possible strategies which can be dependent on the human operator's preference and experience levels.

This is quite a complex set of operations that will be challenging to do or cannot be research on the shop floor itself. In this case, a VR environment such as ours would enable us to construct an environment where a highly skilled operation can take place as well as provide the possibility to investigate how human-robot collaborative strategies could be developed with minimal risk.

The metrics researched in this paper could be used by the human-robot collaborative system to gauge human reactions and attentiveness to the robot as well as to the task being performed. Lessons learnt can then be transferred to an actual shop floor.

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References

[1]. Michalos, G., Makris, S., Tsarouchi, P., Guasch, T., Kontovrakis, D. and Chryssolouris, G., 2015. Design considerations for safe human-robot collaborative workplaces. Procedia CIrP, 37, pp.248-253.

[2]. Heyer, C., 2010, October. Human-robot interaction and future industrial robotics applications. In 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 4749-4754). IEEE.

[3] Silva, L., Tennakoon, T.M., Marques, M. and Djuric, A.M., 2016. Baxter Kinematic Modeling, Validation and Reconfigurable Representation (No. 2016-01-0334). SAE Technical Paper.

[4] Rethink robots. (2018). Swayer. [online] Available at: http://www.rethinkrobotics.com/sawyer/ [Date Accessed] 16/02/2018.

[5] FANUC. (2016). Small Collaborative Robot. Available at: http://www.fanucamerica.com/cmsmedia/datasheets/Compact%20CR%20line%20up%20product%20information_251.pdf [Date Accessed] 16/02/2018.

[6]. Gleeson, B., MacLean, K., Haddadi, A., Croft, E. and Alcazar, J., 2013, March. Gestures for industry: intuitive human-robot communication from human observation. In Proceedings of the 8th ACM/IEEE international conference on Human-robot interaction (pp. 349-356). IEEE Press.

[7]. Michalos, G., Makris, S., Spiliotopoulos, J., Misios, I., Tsarouchi, P. and Chryssolouris, G., 2014. ROBO-PARTNER: Seamless Human-Robot cooperation for intelligent, flexible and safe operations in the assembly factories of the future. Procedia CIRP, 23, pp.71-76.

[8]. Tsarouchi, P., Makris, S. and Chryssolouris, G., 2016. Human–robot interaction review and challenges on task planning and programming. International Journal of Computer Integrated Manufacturing, 29(8), pp.916-931.

[9]. Bannat, A., Gast, J., Rehrl, T., Rösel, W., Rigoll, G. and Wallhoff, F., 2009, July. A multimodal human-robot-interaction scenario: Working together with an industrial robot. In International Conference on Human-Computer Interaction (pp. 303-311). Springer, Berlin, Heidelberg.

[10]. Tsarouchi, P., Matthaiakis, A.S., Makris, S. and Chryssolouris, G., 2017. On a human-robot collaboration in an assembly cell. International Journal of Computer Integrated Manufacturing, 30(6), pp.580-589.

[11]. Michalos, G., Karagiannis, P., Makris, S., Tokçalar, Ö. and Chryssolouris, G., 2016. Augmented reality (AR) applications for supporting human-robot interactive cooperation. Procedia CIRP, 41, pp.370-375.

[12]. Tahriri, F., Mousavi, M., Yap, H.J., Siti Zawiah, M.D. and Taha, Z., 2015. Optimizing the robot arm movement time using virtual reality robotic teaching system. International Journal of Simulation Modelling, 14(1), pp.28-38.

[13]. Crespo, R., García, R. and Quiroz, S., 2015. Virtual reality application for simulation and off-line programming of the mitsubishi movemaster rv-m1 robot integrated with the oculus rift to improve students training. Procedia Computer Science, 75, pp.107-112.

[14]. Rao, Y., Xu, B.L., Jing, T., Zhang, F. and Zhao, X.Y., 2017. The Current Status and Future Perspectives of Virtual Maintenance. Procedia Computer Science, 107, pp.58-63.

[15]. Ren, L., Zhang, L., Wang, L., Tao, F. and Chai, X., 2017. Cloud manufacturing: key characteristics and applications. International Journal of Computer Integrated Manufacturing, 30(6), pp.501-515.

[16]. Al-Ahmari, A.M., Abidi, M.H., Ahmad, A. and Darmoul, S., 2016. Development of a virtual manufacturing assembly simulation system. Advances in Mechanical Engineering, 8(3), p.1687814016639824.

[17]. Berg, L.P. and Vance, J.M., 2017. Industry use of virtual reality in product design and manufacturing: a survey. Virtual Reality, 21(1), p.1.

[18]. Matsas, E. and Vosniakos, G.C., 2015. Design of a virtual reality training system for human-robot collaboration in manufacturing tasks. International Journal on Interactive Design and Manufacturing.

[19]. Phoon, S.Y., Yap, H.J., Taha, Z., Pai, Y.S., Phoon, S.Y., Yap, H.J. and Taha, Z., 2017. Interactive solution approach for loop layout problem using virtual reality technology. The International Journal of Advanced Manufacturing Technology, 89(5-8), pp.2375-2385.

[20]. Petti, A., Hutabarat, W., Oyekan, J., Turner, C., Tiwari, A., Prajapat, N. and Gan, X.P., 2016. Impact of model fidelity in factory layout assessment using immersive discrete event simulation.

[21]. Hutabarat, W., J Oyekan, Turner, C., Tiwari, Al, and Prajapat, N., 2016. Proceedings of the 2016 Winter Simulation Conference, Washington DC, USA.

[22]. Monica, Z., 2015. Optimization of the production process using virtual model of a workspace. In IOP Conference Series: Materials Science and Engineering (Vol. 95, No. 1, p. 012102). IOP Publishing.

[23]. Yap, H.J., Taha, Z., Dawal, S.Z.M. and Chang, S.W., 2014. Virtual reality based support system for layout planning and programming of an industrial robotic work cell. PloS one, 9(10), p.e109692.

[24]. Kuts, V., Modoni, G.E., Terkaj, W., Tähemaa, T., Sacco, M. and Otto, T., 2017, June. Exploiting Factory Telemetry to Support Virtual Reality Simulation in Robotics Cell. In

International Conference on Augmented Reality, Virtual Reality and Computer Graphics (pp. 212-221). Springer, Cham.

[25]. Knight, W., 2013. Smart Robots Can Now Work Right Next to Auto Workers. MIT Techonology Review. Available at: https://www.technologyreview.com/s/518661/smart-robots-can-now-work-right-next-to-auto-w [Accessed March 28, 2017].

[26]. Rustici, C., 2015. Who Cares About Robots?The Rise of Cobotics. DirectIndustry e-magazine. Available at: http://www.directindustry.com/emag/hannover-messe-2015/robots-who-cares-about-cobotics-9031.html.

[27]. Cho, C.N., Kim, J.H., Lee, S.D. and Song, J.B., 2012. Collision detection and reaction on 7 DOF service robot arm using residual observer. Journal of mechanical science and technology, 26(4), pp.1197-1203.

[28]. Tan, J.T.C., Duan, F., Kato, R. and Arai, T., 2010. Safety strategy for human–robot collaboration: Design and development in cellular manufacturing. Advanced Robotics, 24(5-6), pp.839-860.

[29]. Sanderud, A., Thomessen, T., Osumi, H. and Niitsuma, M., 2015. A Proactive Strategy for Safe Human-Robot Collaboration based on a Simplified Risk Analysis. Modeling, Identification and Control, 36(1), p.11.

[30]. Kulić, D. & Croft, E., 2007. Pre-collision safety strategies for human-robot interaction. Autonomous Robots, 22(2), pp.149–164.

[31]. Makris, S., Michalos, G. and Chryssolouris, G., 2012. Virtual commissioning of an assembly cell with cooperating robots. Advances in Decision Sciences, 2012.

[32]. ABB. 2017. Product Specification, IRB 2600. ABB AB, Robotics Robotics and Motion Se-721 68 Västerås Sweden.

[33]. Maurice, P., Padois, V., Measson, Y. and Bidaud, P., 2016. Experimental assessment of the quality of ergonomic indicators for dynamic systems computed using a digital human model. International Journal of Human Factors Modelling and Simulation, 5(3), pp.190-209.

[34]. ExRx.net LLC, 2017. Body Segment Data. Available at: http://www.exrx.net/Kinesiology/Segments.html [Accessed April 11, 2017].

[35]. Ogorodnikova, O., 2009. How safe the human-robot coexistence is? Theoretical presentation. Acta Polytechnica Hungarica, 6(4), pp.51-74.

[36]. Luo, J., Ying, K. and Bai, J., 2005. Savitzky–Golay smoothing and differentiation filter for even number data. Signal Processing, 85(7), pp.1429-1434.