CRANFIELD UNIVERSITY

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The Development of a Human-Robot Interface for Industrial Collaborative System

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ABSTRACT

Industrial robots have been identified as one of the most effective solutions for optimising output and quality within many industries. However, there are a number of manufacturing applications involving complex tasks and inconstant components which prohibit the use of fully automated solutions in the foreseeable future.

A breakthrough in robotic technologies and changes in safety legislations have supported the creation of robots that coexist and assist humans in industrial applications. It has been broadly recognised that human-robot collaborative systems would be a realistic solution as an advanced production system with wide range of applications and high economic impact. This type of system can utilise the best of both worlds, where the robot can perform simple tasks that require high repeatability while the human performs tasks that require judgement and dexterity of the human hands. Robots in such system will operate as “intelligent assistants”.

In a collaborative working environment, robot and human share the same working area, and interact with each other. This level of interface will require effective ways of communication and collaboration to avoid unwanted conflicts. This project aims to create a user interface for industrial collaborative robot system through integration of current robotic technologies. The robotic system is designed for seamless collaboration with a human in close proximity. The system is capable to communicate with the human via the exchange of gestures, as well as visual signal which operators can observe and comprehend at a glance.

The main objective of this PhD is to develop a Human-Robot Interface (HRI) for communication with an industrial collaborative robot during collaboration in proximity. The system is developed in conjunction with a small scale collaborative robot system which has been integrated using off-the-shelf components. The system should be capable of receiving input from the human user via an intuitive method as well as indicating its status to the user effectively. The HRI will be developed using a combination of hardware integrations and software developments. The software and the control framework were developed in a way that is applicable to other industrial robots in the future. The developed gesture command system is demonstrated on a heavy duty industrial robot.

Keywords:

Human-robot interface; gesture control; human-robot interaction; system communication; teleoperation; automation; robot assistant

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LIST OF ABBREVIATIONS

ASRD	Affective-State Reporting Device
API	Application Program Interface
AOI	Area of Interest
APF	Artificial Potential Field
ACE	Autonomous City Explorer
BSI	British Standards Institution
CCP	Central Control Programme
CPU	Central Processing Unit
DOF	Degree of Freedom
DHMT	Dynamic Hand Motion Tracking
EEG	Electroencephalogram
FSM	Finite State Machine
GUI	Graphical User Interface
Hz	Hertz
HMI	Human Machine Interface
HRC	Human-robot collaboration
HRI	Human Robot Interface
ID	Identification
IR	Infrared
IP	Ingress Protection
I/O	Input/ Output
IFR	International Federation of Robotics
IP	Internet Protocol
LED	Light-Emitting Diode
LCD	Liquid Crystal Display
OLED	Organic Light-emitting Diode
PCA	Principal Component Analysis
RFID	Radio-Frequency Identification
RGB	Additive Colour Model
RAM	Random-access Memory
RULA	Rapid Upper Limb Assessment
RT	Reaction Time
SDK	Software Development Kit
SPR	Static Pose Recognition
SOI	System of Interest
TFT	Thin-Film Transister
3D	Three-dimensional Space

2D	Two-dimensional Space
TCP	Tool Centre Point
TCP	Transmission Control Protocol
TOF	Time-of-Flight
USB	Universal Serial Bus
VSE	Vision for Space Exploration

PUBLICATIONS

Journal Publication

Tang, G., Asif, S., & Webb, P. (2015). The integration of contactless static pose recognition and dynamic hand motion tracking control system for industrial human and robot collaboration. Industrial Robot: An International Journal, 42(5).

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1 Introduction

The efficiency of a team of human workers is dictated by the effectiveness of communication between teammates. The same applies to human-robot collaboration (HRC). If one does not communicate well with another during cooperation, the operations will result with increased system downtime and errors which may affect the quality and rate of output. Conventional human-robot interfaces enable highly skilled personnel to programme industrial robots using proprietary robot interface and programming languages. However, these methods of robot control were not designed for human-robot collaboration, such applications may require frequent intervention by a human worker with minimal amount of training. Thus, an intuitive and interactive solution is required which is presented in this thesis.

1.1 Research motivation

Industrial robots have been identified as an effective solution for optimising output and quality within many industries such as automotive manufacturers. There are numerous manufacturing processes that could potentially be automated in order to improve efficiency and quality. The use of readily available robotic systems could provide a means of achieving such automation in a cost effective manner. However, there are a number of high-value low-volume manufacturing processes involving large numbers of product variants and complex tasks for example, wing manufacture which prohibit the use of fully automated solutions in the foreseeable future (Walton et al, 2011).

Previous safety regulations require the separation of human operators from automated equipment, typically with fixed safety fencing. Such installations are difficult to arrange on a flexible assembly line, restricting the efficiency of the overall assembly process. However, health and safety standards such as ISO 10218:2 - 2011 have been updated to reflect that in some circumstances it is now safe and viable for humans to work more closely with industrial robots (British Standards Institution, 2011), this, coupled with the introduction of safety rated collaborative robots and improved low cost sensing technology, may now provide an opportunity to increase the degree of automation in such tasks. Robots in such systems could operate as “intelligent assistants” in a shared workspace in which to carry out simple and repetitive tasks or to carry out tasks that require human operators to work in awkward positions and to lift heavy parts with the human operator carrying out tasks that require decision making and the dexterity of the human hands. The presence of such a robot helper could increase production output and provide a better working environment for production workers.

In a collaborative working environment, robots and humans share the same working area, and interact with each other. This type of interaction will require flexible and effective ways of communication and collaboration to avoid unwanted conflicts and errors. Conventional robot user interfaces such as teach pendant enable trained users to programme industrial robots to perform repetitive routine using proprietary languages. However, these user interfaces and programming languages can require significant learning prior to achieving a satisfactory level of competency to operate these machineries. Frequent human intervention can be required in an industrial human and robot cooperating scenario, an incapable user-interface can costs process cycle time and causes errors in operating procedures. This can result with decreased efficiency which defeats the purposes of an automation system. In the field of human-robot interaction, the majority of researches on the interface between human and robot are targeting social robot and mobile robot applications. Human-robot collaboration research in the industrial robot domain are predominantly focusing on improving the safety aspects of this type of systems, but there has been a lack of research effort in user-interface for human-robot interaction in industrial applications. Thus, the development of an intuitive human-robot interface is encouraged. This thesis is attempting to focuses on improving the human-robot interface in terms of robot control as well as indication system.

1.2 Research objectives

The primary aim of this PhD is to develop a Human-Robot Interface (HRI) for communication with industrial collaborative robots during collaboration in proximity. This goal is achieved through development of software programmes and integration of robotic and sensing technologies.

The system should be capable of receiving input from the human user via an intuitive method as well as indicating its status to the user effectively. The HRI will be developed using a combination of hardware integrations and software developments. Software should be developed using a high level programming language for efficacy reasons and a number of relevant algorithms will be developed to process data. The HRI software and the control framework should be developed in a way that is applicable to other industrial articulated arm robots with a similar robot controller programming structure. The developed system will accept contactless input, and therefore a non-contact based sensor will be used.

Industrial human-robot collaboration research involves engineering and social science. The development of such system can require significant resources, both financial and people. Therefore, the scope of this research project is limited to include a number of exploratory studies and developments which demonstrate the development process of an industrial human-robot collaborative system as contribution for future work.

A number of objectives are outlined as follows:

- Problem identification of human-robot interfaces – literature review of existing technologies and researches on human-robot collaboration
- System integration of an industrial collaborative cell which is compliant to safety standards with risk assessment being carried out. - The system is developed in conjunction with a small scale collaborative robot system which has been integrated using off-the-shelf components.
- Preliminary development of different gesture interfaces to investigate their characteristics.

- Further gesture control system development with human factor considerations.
- Demonstration of gesture control interface with potential applications.
- Integration of gesture control with traditional industrial robot arm
- Investigation of robot to human communication and identify problems of conventional systems.
- Develop robot to human communication system and evaluate with human factor experiment.
- Establish suggestions for future work based on findings.

1.3 Contribution to knowledge

The work described in this thesis offers the following contributions:

Three gesture user interfaces were developed for human-robot collaboration. It provides an understanding of different types of gesture control interface and their potential applications in various aspects of human-robot collaboration.

Two different types of gesture control: Static Pose Recognition and Dynamic Hand Motion Tracking were integrated into one system. The integration was demonstrated using a pick and place and a polishing task to demonstrate its potential application in the industry. The work has been published in a journal paper (Tang et al. 2015).

This thesis demonstrates the integration of a gesture command system and a heavy duty industrial robot. It explains the technical challenges of this type of integration and discusses potential applications.

An exploratory experiment was carried out investigating the effect of robot gestures on users' understanding. It highlights the limitations of industrial robots in performing human-like interaction movements. The experiment results have been published in a conference paper (Tang et al. 2014).

It presents the development process of a HRI for industrial human-robot collaborative system with Human Factor considerations. It demonstrates how human factor tools such as RULA can be applied in the system design process.

Human factor experiment was also used to validate the design concept at development stage.

The findings of this thesis suggest a number of future works. This contributes to the initiation of future academic proposals. They also reveal potential research directions for the future.

1.4 Thesis structure

The remainder of the thesis is organised as follows:

Chapter 2 provides the underlying basis by an overview of related work on human-robot collaboration. This chapter introduces collaborative robot and their applications. The issues associated with collaborative systems are explored further which leads to the realisation of the need of better communication in human-robot interaction. Other human-robot collaboration related subjects such as safety and supporting technology are also discussed in the literature review chapter.

Chapter 3 presents the methodologies used to achieve the objectives of this thesis. It describes the problem identification process, hardware selection and integration of a base system for the main development in this thesis.

Chapter 4 presents in detail the development of gesture control systems for robot interaction. It describes the design procedures of gesture control systems at different stages which include design of system architectures, evaluation and system integration.

Chapter 5 presents the development of the Robot to human communication system concepts. This chapter highlights the importance of user feedback within the design process. Thus, it explains in detail the experimentation procedure used in various stages of testing. The experimental results are also presented.

Chapter 6 provides an overview of the work presented in this thesis and discussions regarding this research.

Chapter 7 concludes the work and provides suggestions for future work.

Appendix A provides additional literature review on digital facial expression, robot safety equipment, and the effect of gesture on human’s trust.

Appendix B provides a description of additional research methodology used in this thesis.

2 Literature review

2.1 Introduction

The literature review has focused on human and robot collaboration and interaction. This aims to investigate existing research efforts which have been attempting to solve a similar problem in interactive robotics systems, thus a number of relevant research areas have been identified. A variety of research in similar collaborative contexts has been recognised. However, the majority are based on humanoid type social robots. Various researchers have developed communication methods with small industrial robot arms which aid collaboration, and some preliminary work has been done on robotic collision avoidance with industrial arm robot.

The literature review begins with a brief overview of industrial robots which briefly covers their history and the state of the art. The developments in human-robot collaborative systems is subsequently reviewed, the use of collaborative robots in the industrial is also discussed. It is realised that effective communication is key to achieve seamless collaboration, thus this subject area is extensively reviewed. The HRI of a collaborative system has direct impact on its efficacy of receiving and conveying message with the human counterpart so existing and current developments in HRI are studied. This research concerns collaborative system where a human and a robot coexist in the same work space, safety is one of the main consideration in this type of situations so robot safety is reviewed as well as researches carried out on the subject of human-robot interaction in proximity. The state of the art in sensing technologies used in robotics is also reviewed to support system development.

2.2 Overview

The deployment of industrial robots in manufacturing plants has continued to increase over previous decades. They are used in a variety of applications which include spot welding in automotive production and pick-and-place operation in the packaging industry (Fryman and Matthias, 2012). Traditional industrial robot operations are enclosed by hard safeguard which prohibited human intervention, but there is a shift in paradigm in recent years due to the continuously increasing requirements of flexibility and changes in industrial robot regulations such as ISO 10218-2:2011 (Krüger et al, 2009; British Standards Institution, 2011). Moreover, there are many situations where robots fail to complete a task to a desirable standard due to unexpected events. There are many applications involving objects or processes with high degrees of variability where their positions and orientations are unknown, which complicates the requirement of the robotic system. It is a common issue in high-value low-volume production (Potter, 2009; Inman et al, 1996). Such robotic systems are difficult and expensive to develop, which may defeat the original purpose of using robotic technology. However, it has been recognised that human and robot operating as one system can boost productivity and improve many current processes. In this case, the role of the human operator remains important in the process which reduces the optimal degree of automation to be less than 100% (Fryman and Matthias, 2012). It is important to balance the workload between human and robot to optimise productivity, and studies have been carried out to investigate the optimal level of collaboration between human and robot. A measurement method has been developed in (Bechar et al, 2006), where 4 human-robot collaboration levels from manual to fully autonomous were defined, tested and evaluated.

The introduction of industrial collaborative robots has enabled human and robot to coexist in the same work space (Knight, 2014; Tan et al, 2016). These robots are currently being used in the automotive industry to perform tedious tasks which include sealant application, system installation and material handling (Bernier, 2013; Green, 2013). Industrial collaborative robots feature safety rated designs which limit power and force, and this eliminates the requirement of safeguard (Matthias et al, 2011). Collaborative industrial robots are becoming increasingly popular in last five years. Many robotic companies are developing ‘user friendly’ robots for collaborative tasks. One of the prominent robot manufacturers, ABB Corporate Research has investigated approaches to risk assessment for collaborative robots and a more detailed future methodology that will improve resolution to relevant low-level injury risks (Matthias et al, 2011). The focus is on designing robot with low health impact to the user in the event of collision between the 2 agents. The collaboration of human operator and traditional large industrial robot has been investigated for aerospace production application previously. Walton et al from Cranfield University have studied the implementation of human and robot cooperation in an aerospace equipping process in (Walton et al, 2011) .The project developed a system using a high payload KUKA robot to perform positioning with actual aerospace components. The human interaction area was monitored with the state of the art safety monitoring devices, which include a 3D safety camera and a safety laser scanner. This work has shown that human and robot collaborative tasks can be performed safely and effectively in the heavy industry.

The growing interest of industrial human-robot collaboration has sparked a number of related research areas Where a Human and a robot coexist in the same workspace can introduce additional safety risks when compared to fully automated system guarded within a cage. Risk assessment for collaborative robots must be considered with high priority during the implementation of this type of systems, viable approaches have been investigated in existing researches (Matthias et al, 2011). Apart from risk assessment, studies have been carried out in developing alternative safety strategies for industrial robots such as safety path planning and collision avoidance (Pedrocchi et al, 2013; Sharma et al, 2015). When carrying out a collaborative task, the communication between human and robot must be effective in order to achieve seamless collaboration. Ideally, a robot should collaborate with non-expert users with little to no prior training. This can be accomplished by incorporating intuitive human-robot interface. The reduced cost of advanced 3D sensors has enabled the development of intuitive human-robot interface such as contactless gesture control (Tang et al, 2015). Furthermore, haptic devices are also a popular tool for robot control in recent researches (Vu and Na, 2011). The ability to perceive a robot’s state during a collaborative work task is also paramount for users to be aware of the situation and make confident planning of their own actions. This can increase the fluency of a process and reduce hazardous conditions. A number of studies have been carried out in this context, which includes robot gesture, anticipation and hesitation motion, dialog control, and touchscreen display (Tang et al, 2014; Moon et al, 2011; Gielniak and Thomaz, 2011).

The development of human-robot collaboration should also be considered from a human factor perspective. For example, the balance of workload between human and robot can be used to optimise productivity (Bechar et al, 2006; Hinds et al, 2004). Understanding the preferences of the human worker can improve planning of collaborative task (Gombolay et al, 2015). Measurement of users' trust in a robot can be used in enhancing system design (Sadrfaridpour et al, 2014; Freedy et al, 2007).

The literature review of human-robot collaboration is discussed in greater detail in following chapters sorted by relevant research areas.

2.3 Industrial robot

Unimate is the first modern-day industrial robot, co-developed by serial entrepreneur George Devol who applied for a patent in 1954 and received the patent by 1961 (figure 2-1). The Unimate arm was commissioned on the General Motors assembly line in 1961 to pick and place hot die-cast metal components from their molds *(Pearce, 2011; Ballard, 2011)*. In the early 1970s, Nissan Corporation automated an entire assembly line with robots which sparked a continuous revolution. An industrial robot has three crucial elements. It manipulates its physical environment, industrial robots are computer controlled and they operate mostly in industrial setting, such as production line. Industrial robots are broadly applied in manufacturing operations which include assembly, machining, welding, packaging, palletising, material handling and positioning *(Thrun, 2004)*.

Figure 2-1 - Unimate robot

The use of industrial robots has continued to expand and sales have increased in current industries. The International Federation of Robotics (IFR) estimated that around 225,000 units were sold in 2014 which is 27% more than in 2013 (IFR, 2014). Industrial robot systems can integrate with other factory automation systems to support just-in-time production and economically-viable bespoke manufacturing. A well-design robotised manufacturing line can adapt to produce different product variants as demand dictates (Heyer, 2010). There has been a shift in paradigm from low cost high-volume production to high value low-volume manufacturing and increased production demand in wage-intensive countries which mean manufacturing systems require more flexibility, adaptability and cost-efficiency (Jovane et al, 2003).

Figure 2-2 - articulated robot (top left); parallel robot (bottom left); Cartesian robot (top right); SCARA robot (bottom right)

There are four popular types of industrial robots which are widely available on the current market, these include: articulated robot, parallel robot, Cartesian robot, and SCARA robot (as illustrated in figure 2-2). Amongst these four types, articulated robot is the most widely used in manufacturing industry due its good flexibility, speed, and large working envelope (as illustrated in figure 2-3)(IFR, 2012). Robot manufacturers generally classify these robots by their payload and reach capabilities into 3 main groups which are small, medium and large. Small robots have payload of up to 16kg and some manufacturers offer variants of small robots with extended reach of up to 3.1m. Medium robots have payloads of between 16-60kg and reach of around 3m. Large robots have payloads of 60+kg and reach of over 3m.

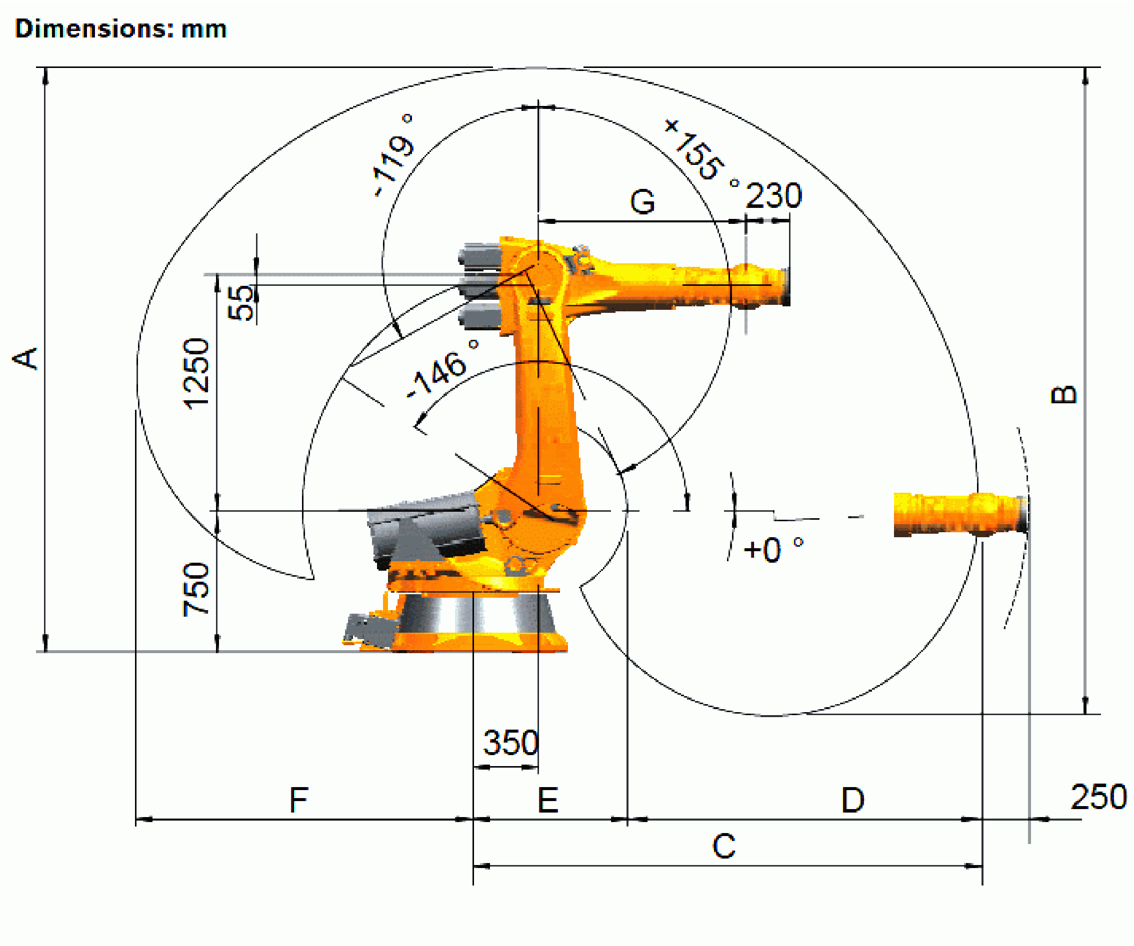


Figure 2-3 - typical working envelop of an articulated robot

Traditional industrial robots have high payload capability and repeatability, but they have never been safe for human to work alongside them. Thus, the majority of final assembly tasks in automotive and aerospace manufacturing have remained full manual procedures (Knight, 2013; Webb, 2011). The goals of human-robot collaboration are to increase productivity and reduce workers' workload by relieving them of the most unpleasant jobs. Thus, industrial robots become an essential element of many manufacturing systems (High Level Group, 2006). Collaborative robots or Cobots are introduced to the market in recent years. These robots are designed to work along humans without the requirement of additional safe guard which reduce the complexity and cost for implementation.

2.3.1 Collaborative robot

There is a wide range of small articulated robots on the market, and most of them have similar capabilities. A number of the most prominent robot suppliers have been consulted during the process of identifying the most suitable robot for this application, and these include KUKA, FANUC, ABB, Yaskawa Motoman, Kawasaki and Comau.

Recently, a new breed of collaborative robots are unveiled on the market, these robots are designed to work alongside human and with each other without the requirement of safe guarding. A common feature among these robots is the compliant design which greatly reduces the severity of injury in the event of a collision between human and robot. Collaborative robots are offered by a number of manufacturers in single-arm and dual-arm configurations, 6-axis or 7-axis, for example KUKA LWR (Bischoff et al, 2010), Universal Robots (Østergaard et al, 2006), ABB YuMi and Baxter Robot (Guizzo and Ackerman, 2012; Anandan, 2013).

Rethink Robotics has created the Baxter robot, which was designed to be a human friendly robot (figure 2-4). The Baxter robot features an animated eye Human Machine Interface (HMI), as well as a dual arm system driven by series elastic actuators (Rethink Robotics, 2015). The key feature of the robot is its compliance provided by the actuators, which allow safe interaction, but it has relatively low repeatability and maximum speed. However, these robots have inferior capabilities compare to traditional industrial robots which restricts their applicability in large scale applications.

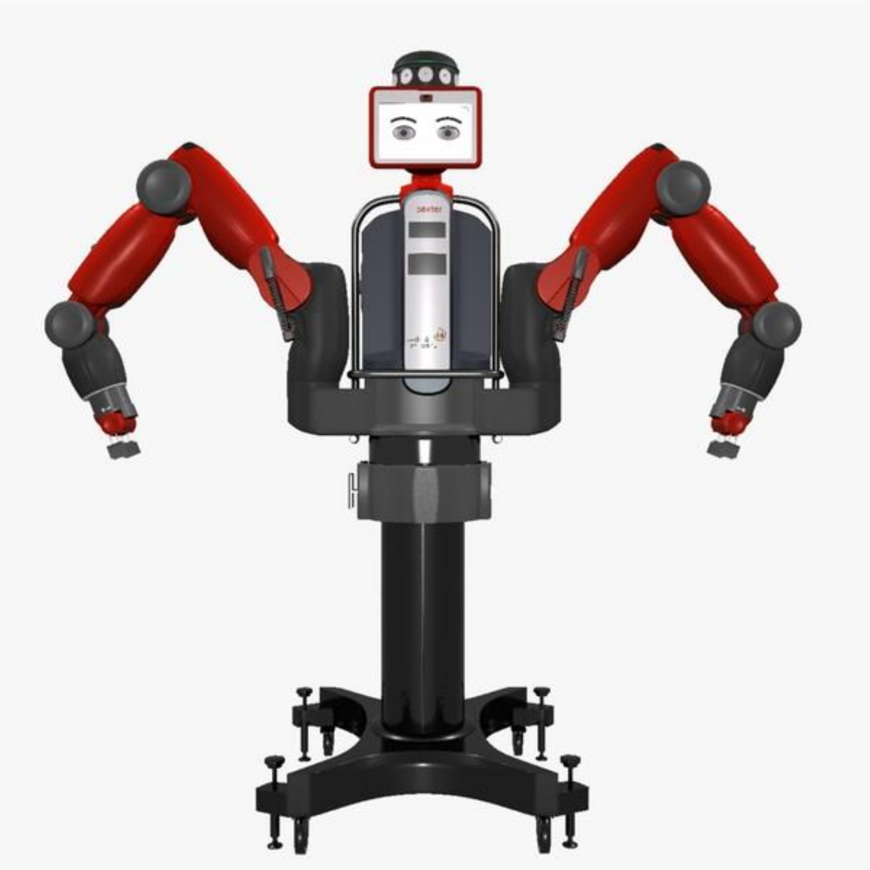


Figure 2-4 - Baxter robot

ABB has developed YuMi, a robot for human-robot collaboration in the same workspace. The robot features inherent safety for human operators, high flexibility and degree of freedom, intuitive interface for programming and deployment, and dexterity which enables it to assemble small parts (Kock et al, 2011; Hedelind and Kock, 2011). The ABB YuMi comprises a two-arm robot with integrated controller inside its torso (figure 2-5). Each of its arms has seven joints and each arm is equipped with a multi-tooled gripper which is developed for the targeted applications (Vittor et al, 2011; Park et al, 2012).

Figure 2-5 - ABB YuMi robot

The light-weight robots developed at the German Aerospace Centre (DLR) features low inertial properties, torque sensing in each joint and a human-like load to weight ratio (Albu-Schäffer et al, 2007). A technology transfer was undertaken between KUKA and DLR towards the end of the research stage carried out in DLR (Bischoff et al, 2010), and the KUKA LWR was developed (figure 2-6). The properties of the LWR enable them to fit into applications which require the robot to interact with human. A safety evaluation of this particular robot has been carried out by Haddadin et al (2007) which concluded the light-weight robot does not cause serious ham.

Figure 2-6 - KUKA LWR

As a result of further research, the Universal Robot UR5 robot has been chosen for this project (figure 2-7). This robot has 5kg payload, +/-0.1mm repeatability and 850mm reach, which is adequate to perform simple assembly tasks of a small structure for experiments and testing. However, this robot was chosen mainly for its safety features. The UR5 robot is a safety rated robot equipped with a post-collision safety function which will activate an emergency stop to the robot as soon as an impact has been detected. That means the user can interact with the robot freely without any safe guarding, and that has greatly simplified the work cell integration and also allows collaborative experiments to be carried out with less restriction.

Figure 2-7 - Universal Robot UR5

2.4 Human and Robot Collaboration

There has been an increased interest in the technology aspect and economic benefit of bringing human and robot closer together in manufacturing environment. The primary motivation is the limitations of conventional robots in tasks which require a certain level of perception, dexterity and reasoning, this can be difficult to achieve technically in a cost-effective manner. In a high value low-volume manufacturing environment with elevating cost pressure, the conflict between flexibility and automation has become apparent. With the increased flexibility requirements, a fully automated solution may no longer be optimal in terms of cost, productivity, robustness and flexibility. In this case, a safe and flexible collaboration between human and robot can be a feasible solution to achieve maximised productivity and flexibility. Thus, industrial robots can operate as intelligent assistants in production environment at handling, machining, positioning and assembly tasks (De Santis et al, 2008; Hägele et al, 2002; Helms et al, 2002; Krüger et al, 2009).

Automation has provided many benefits for a broad range of applications. The main benefit of automation regardless of applications is that it can reduce the human user’s workload, both mentally and physically (Boy, 1998). These workload reductions can include response execution and muscular exertion, decision making, and in information acquisition and analysis. The potential for automation to reduce workload is the main attractive point to the human operator in an environment where time stress is high or in task where cognitive effort must be minimised for carrying out other concurrent tasks. However, the workload-reducing feature can induce new types of problems while reducing some other errors (Pritchett, 2009; Sarter, 2008). If not designed correctly, automation may increase rather than decrease human mental workload (Wiener and Curry, 1980).The main goal of the developed system in this project is simple and flexible programming, as most people who interact with an industrial robot system are production operators and not robotic experts. Thus, an intuitive and natural user interface is important for seamless human-robot collaboration (Hvilshøj et al, 2012). Human-robot interaction in proximity can be carried out efficiently with the support of innovative interface such as gesture control (Krüger et al, 2010; Stopp et al, 2001; Burger et al, 2008). The development of human-robot collaboration has become more viable in recent years due to the significant decrease in costs of devices for computation, sensing and actuation. Furthermore, recent advances in industrial robots have enhanced their potential to operate in unstructured and high variability environment (Thrun, 2004).

Many functions in collaborative systems are shared by humans and robots, thus it is important to consider synergies and conflicts among the various performers of joint actions. Furthermore, it has been realised that successful function allocation is not a simple process of transferring responsibilities from one agent to another (Boy, 1998). It has been found that automated assistance does not simply enhance human’s ability to perform a task, but instead changes the nature of the task itself (Christoffersen and Woods, 2002; Norman, 1992). Research on human-automation interaction has shown that automation can change the cognitive process of a human user, in a way that is unanticipated by the system designers. Furthermore, a technology-centred approach has been the cause for many human performance issues and accidents when using automated systems such as Three Mile Island accident and Kegworth air disaster. Designers have typically focused on improving the technology aspects of an automated system without taking human factor into consideration. Research evidences have shown that a human-centred design approach should be incorporated when considered an automated system, in which the design objective is for joint human-automation performance (Billings, 1996; Lee and Seppelt, 2009).

Industrial Psychologists have classified automation in terms of which human performance functions it replaces. Five general categories have been suggested to describe the different purposes of automation as follows (Parasuraman and Sheridan, 2000):

- Tasks that humans cannot perform
- Human performance limitations
- Augmenting or assisting Human Performance
- Economics
- Productivity

The categories can be a useful tool for assignment of new task to different team players of the system. Furthermore, Joint activity theory mentions three points for effective coordination which are interpredictability, common ground, and directability (Klein et al, 2005). Interpredictability is the ability of team players to predict the actions of others in order to plan their own actions. In this context, the users must be aware of the robot's state to avoid interruption to the operation. Common ground refers to the relevant mutual knowledge which supports the collaborative task. For example, two members of a team cannot cooperate effectively unless they can make effective assumptions of each other's capability. Directability is the capacity to redirect the actions of other team members in a collaborative task as the conditions and priorities change. In this case, the robot system must have the capability to receive input from users during a task and response accordingly (Klein et al, 2005; Bradshaw et al, 2009).

The level of autonomy can affect the efficiency of a human-robot collaborative system depending on the nature of the task. It is important to perform a cost and benefit analysis associated with automation and manual control to find the optimal level of autonomy. A manual system allows high level of system control, but it is labour intensive and the capability of robot may not be fully utilised. A fully automated system lacks the flexibility of high-level task planning and execution to tackle uncertainties within the process which necessitates frequent human intervention to alter the programme. Sophisticated interfaces which enable human guidance of robots' tasks and goal can be used to tackle these issues (Few et al, 2006; Bruemmer et al, 2005). It has been suggested that an adaptive and variable approach can be used to address the issue (Goodrich et al, 2007).

One of the most important variables in human-robot collaboration is trust. There are numerous literatures on trust and its application on automation, for example the concepts of complacency (over-trust) and the cry wolf effect (under trust) have been introduced by Sorkin (1989). Automated systems that appear to be reliable can cause the tendency for operators to not monitor the automation or the signals from the system. Automation complacency allows human operators to focus on their other tasks before the machine eventually fails, but when it fails there can be two behavioural consequences. Firstly, the machine failure is infrequent and therefore unexpected so it will be hard to detect when it occurs. Secondly, the human operator who expects the machine to be functioning properly will be less likely to monitor the machine operations which can results in a lack of situation awareness (Endsley and Kiris, 1995). Thus, the operator may not react appropriately when an error occurs. More recent work has been carried out on developing a trust scale for evaluating the level of trust for collaborative robotic systems (Charalambous et al, 2015).

There is a vast body of research on human-robot cooperation particularly in material handling. Maeda et al (2001) have investigated in a control method for human-robot cooperative manipulation. Agrevante et al (2014) proposed a framework for combining vision and haptic information for human-robot interaction. The system is aim at tasks which cannot be performed with vision or haptic information alone (Agravante et al, 2014; Bussy et al, 2012). Effort has also been made to improved fluency of robot-human hand-overs by using spatial contrast (Cakmak et al, 2011).

2.5 Collaborative robot in manufacturing environment

BMW has progressed towards revolutionising the role of industrial robots in automotive production by deploying a number of robots which work alongside human workers at its plant in Spartanburg South Carolina. Compliance industrial robots are used in a door sealant application task prior to door casing installation (as illustrated in figure 2-8). The task involves rolling of glue lines to an automotive door which is heavy duty work so the aim of assembly robots is to improve the working condition of the workforce instead of replacing them. The age of skilled workers and retirement age have continued to increase, thus it is important to compensate with the help of industrial robots and maintain the health of the workforce. BMW's human-robot collaboration is one of the first of many examples of robot working in proximity with humans. BMW is currently testing mobile assembly robots which are capable of collaborating directly with human workers. These robots are being developed with Julie Shah, a professor in MIT's department of aeronautics and astronautics (Knight, 2013).

Figure 2-8 - industrial collaborative robot applying sealant on car door

Volkswagen deployed its first Universal UR robot in 2013 to install glow plugs into engines. Manual workers are working with the robot on the same production cell as shown in figure 2-9 (Rustici, 2015).

Figure 2-9 - industrial collaborative robot carrying out glow plug installation

On the other hand, Mercedes-Benz began collaborating with KUKA AG in 2012 to investigate the use of the KUKA Lightweight Robot on its manufacturing line (figure 2-10). It is suggested the lightweight robot can operate as a worker's "third hand" which can be set up to support workers ergonomically. The plan is for the robots to take over tiring and repetitive tasks (Daimler, 2012).

Figure 2-10 - KUKA LWR in series production

Audi has deployed the “PART4you” cooperative robots at its main plant in Ingolstadt in 2015. The robots operate as material handler which hand automotive components to workers when required (figure 2-11). Similar to the Mercedes-Benz concept, the robots work alongside human workers without any safety barrier, and they pick up components from a box and pass them to assembly workers at the right time and in an ergonomically optimal position. The robots feature a soft protective skin with integrated safety sensors to minimise hazard to employees (Audi press release, 2015).

Figure 2-11 - collaborative robot is currently being used in Audi factory

2.6 Communication in collaboration

It is identified that communication between human and robot must be effective in order for a collaborative task to be carried out smoothly. Existing studies have investigated the communication between humans and robots during a collaborative task. The computer science department of the University of Southern California has develop a collaborative communication framework, which was inspired by Theory of Mind and making use of perspective taking to support several collaborative functions, including detection of opportunities to assist. The work is currently under development and their aim is to validate the approach on a cooperative task in a dynamic environment involving humans and robots (Clair and Mataric, 2011). The efficiency of a collaborative task can also be improved by designing smooth and natural cooperative transfers performed by a human-robot system. In (Ahmad F et al, 2011), the effect of perceiving different parts of the object as a means for exchanging information between subjects has been investigated, as well as the importance of having task initiation signal and information of targets position to improve the task smoothness.

It is important for users to be able to perceive a robot’s state during a collaborative work task, so users can be aware of the situation and make confident planning of their own actions. This can increase the fluency of a process and reduce hazardous conditions. A number of studies have been carried out in this context, which includes robot gesture, anticipation and hesitation motion, dialog control, and touchscreen display.

It is logical to consider human-human communication when developing a human-robot communication interface. Many research projects have studied human interaction prior to investigate human-robot collaboration (Nakata et al, 2011; Meisner et al, 2009; Zhu and Kaber, 2012). Literatures on human-human communication are briefly reviewed to gain a basic for the understanding of the needs of an effective human-robot collaborative system. In face-to-face communication, people use speech, gesture, gaze and non-verbal cues to effectively communicate with each other. Eye gazes are an important subset of non-verbal communication cues, it provides visual feedback which regulates the flow of conversation, communicating emotion and relationships, and improving concentration by restriction visual input (Kendon, 1967; Breazeal et al, 2005). Eye gaze cues are also valuable for coordinating collaborative task (Fussell et al, 2000; Brennan et al, 2008). Eye gazes have also been found to be useful in task such as human-robot handovers (Admoni et al, 2014; Moon et al, 2014; Sato et al, 2016). Apart from gaze, humans also use a wide range of non-verbal cues to improve communication which include nodding (Cassell and Thorisson, 1999), gesture (Goldin-Meadow et al, 2001; McNeill, 1992; Goldin-Meadow, 1999; Iverson and Goldin-Meadow, 1998) and posture (Strabala et al, 2013). This suggests that a robot needs the capability to recognise and produce non-verbal communication cues in order collaborate effectively with a human partner. Green et al (2008) have classified three types of communication channels which include audio, visual and environmental. “Environment channels consist of interactions with the surrounding world, while audio cues are those that can be heard and visual cues those that can be seen”. Rani et al (2004) developed a robot system that senses and monitors the anxiety level of a human and response accordingly. When the robot and human are collaborating, the robot can detect the emotional state of the human through physiological responses that are generally involuntary which are non-bias from culture, gender or age (Rani et al, 2004).

Moon et al (2011) have investigated the communicative capabilities reflected in the trajectory characteristics of hesitation gestures during human-robot collaboration. The research was addressing the problem of safe interaction for non-expert users of robotic assistants. Hesitation gestures and non-hesitation human arm motions were recorded from simple reach and withdraw tasks and programmed into a 6 degree of freedom (dof) articulated robot. Hesitation gestures of both the human and robot were recognised by the majority of the survey participants, which indicates that hesitation movement from robot can be an effective communication mechanism to express a robot's state of uncertainty during collaborative task. Similar studies have been carried out in (Dominey et al, 2008; Gielniak and Thomaz, 2011), where they created anticipatory motion in robot motion to give users greater time to respond during an interactive task. The concept is that the human partners are aware of the robot's intent earlier so they can react accordingly. The developed algorithms for generating anticipation in robot motion have been tested, but there were limitations with the robot's kinematics so the researches are still on-going.

The importance of clarifying how humans actually interact with each other when they do collaborative work is commonly recognised to be key in creating a human-collaborative robot system. The user should be able to effectively command a robot when intervention is required. There is various existing research which investigates the way humans communicate with each other during human-human collaborative tasks. Many have studied speech command related subjects for the realisation of voice control in collaborative robots. For example, in (Huichi et al, 2011) the effectiveness of the length of a command speech is studied, and based on the experiment results, the authors have proposed three stages of language skill acquisition in collaborative work. Other studies such as (Kruijff et al, 2010, Burger et al, 2011, and Mashimo et al, 2016) have looked at using dialogue and speech to control a robot during collaboration. Attamimi et al (2016) have studied the use of honest signals in robot to improve interaction with human.

Ende et al (2011) have developed a different approach for human and robot communication within collaborative working processes. The authors have reviewed some previous interactive methods which includes a touchscreen display to control the robot state. They have pointed out the drawback of a touchscreen method is the distraction from the actual interaction task, hence a gesture based approach is more suitable for collaborative tasks. It was proposed that human gesture communication skill can be transferred onto an articulated-arm robot. It is realised that the robot's pure task motion does not provide sufficient information to the human to fully understand the task state, so they have studied gestures from human-human interaction and transferred a pre-selected ensemble of gestures to single arm robotic system. Their experimental results have shown that some gestures are better received than others. For instance, synchronising gestures such as "higher" or "lower" have shown poor results, and on the other hand, referencing gestures e.g. "this one" and terminating gestures e.g. "stop" have shown provide valuable information to the human user for their designed use-case. This project will further investigate human and robot communication in collaborative tasks based on the work described above.

2.6.1 Feedback on automation states and behaviours

During a collaborative task, the human operator and robot work together as a team and if one does not communicate with another effectively the task performance will be affected, or accidents may occur. The deficiency of automation feedback to human has been well-documented as one of the most common causes for incidents occurred during a collaborative task.

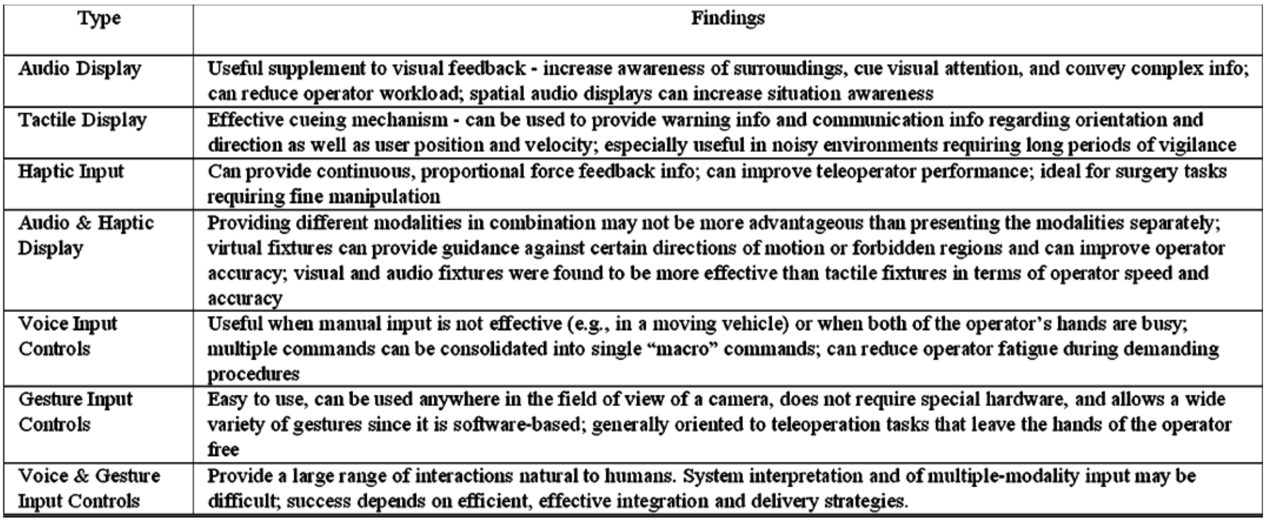
Automation should provide feedback on its state to enable a human operator to predict their next move, but even if feedback is presented the saliency must be high enough for the operators to notice, because human's limitation in signal detection and vigilance capabilities. Humans suffer the phenomenon of change blindness when they are focused on other tasks (Simon and Chabris, 1999) and unexpected signals can often be ignored (Starter et al, 2007).

A typical automated system consists of at least one type of Human Machine Interface (HMI). The HMI includes the electronics required to signal and control the state of industrial automation equipment. These interface products can range from a basic light-emitting diode (LED) status indicator to a thin-film transistor (TFT) panel with touchscreen interface (Atmel, 2015). A traditional industrial robot system usually includes a teach pendant and a stack light to provide user with the information of robot’s state (Electro-Matic, 2015). Some robots have different feedback system, for example the Baxter robot has a monitor screen positioned above its dual-arm and single-arm systems, and a pair of animated eyes is displayed on the screen during an operation to indicate the robot’s state. Rodney Brooks of Rethink robotics has claimed that the face was the most intuitive way for robot to communicate with user (Rethink Robotics, 2015). There are a number of studies investigating the effectiveness of digital facial emotions such as emoticons as described in appendix A1. Others have studied the generation of facial expression for robots and these include (Han et al, 2013; Baltrušaitis et al, 2010; Wu et al, 2009), but there is still a lag of empirical evaluations of human-robot affective interaction, as well as in importing existing tools from avatar animation towards their use of robots.

2.7 Human-Robot interface

NASA published the “Vision for Space Exploration (VSE)” in 2004, a framework that describes the guiding principles and roadmap to implement a robust space exploration program (NASA, 2004). The main goal of the VSE is to implement a sustained and affordable human and robotic program to explore the solar system. The development of joint human-robot systems is a major emphasis to the VSE (NASA. 2005). The use of robot systems was proposed in the VSE due to its capability to perform tasks that are not practical or necessary for humans to perform. It is realised that there is a need for standardisation of human-robot interface because the combination of non-expect robot user and complex and inconsistent robot interfaces will result in significant training requirement, system deficient and increased crew workload. Some human-robot interfaces, such as text-based command, offer great functionality and flexibility but require high learning cost. Other interfaces, such as direct manipulation display are easy to use due to the minimal assumptions on user's knowledge. However, the effectiveness of an interface depends solely on the design. In the design of computer user interface, a sequential approach is often used. Some of the broadly used design methods are heuristic design, guidelines and iterative design (Ferketic et al, 2006).

The traditional setting of industrial robots can be simplistic, inflexible and costly, but that can change with the introduction of human-robot collaborative systems. This type of system can be configured to have wider-domain and less application–specific robots. A generic design with easily reconfigurable user interface will require minimal effort by programme-engineers on site to cover various contexts of operation. Ideally, a robot should collaborate with non-expert humans with little to no prior training. This can be achieved by intuitive robot tuition by demonstration, imitation and explanation (Argall et al, 2009; Nehaniv and Dautenhahn, 2007; Wrede et al, 2013; Molina-Tanco et al, 2005). There is significant research on human-robot interface and manipulation, many of these research studied robot manipulation by imitation of human movement. Gu et al (2011) proposes a two-phase learning framework for human-robot collaborative manipulation task where the robot learns table-lifting skill from a human partner. Further research evidences have shown that communication effectiveness can be maximised when interactive robots have natural language capabilities (van der Zant and Wisspeintner, 2007; Foster et al, 2006; Mavridis and Roy, 2006; Giuliani and Knoll, 2011). Chen et al (2007) studied the human performance issues in relation to user interface design. The advantages of audio, tactile, haptic and gesture interfaces are summarised in figure 2-12.



Type	Findings
Audio Display	Useful supplement to visual feedback - increase awareness of suroundings, cue visual attention, and convey complex info; can reduce operator workload; spatial audio displays can increase situation awareness
Tactile Display	Effective cueing mechanism - can be used to provide warning info and communication info regarding orientation and direction as well as user position and velocity; especially useful in noisy environments requiring long periods of vigilance
Haptic Input	Can provide continuous, proportional force feedback info; can improve teleoperator performance; ideal for surgery tasks requiring fine manipulation
Audio & Haptic Display	Providing different modalities in combination may not be more advantageous than presenting the modalities separately; virtual fixtures can provide guidance against certain directions of motion or forbidden regions and can improve operator accuracy; visual and audio fixtures were found to be more effective than tactile fixtures in terms of operator speed and accuracy
Voice Input Controls	Useful when manual input is not effective (e.g., in a moving vehicle) or when both of the operator's hands are busy; multiple commands can be consolidated into single "macro" commands; can reduce operator fatigue during demanding procedures
Gesture Input Controls	Easy to use, can be used anywhere in the field of view of a camera, does not require special hardware, and allows a wide variety of gestures since it is software-based; generally oriented to teleoperation tasks that leave the hands of the operator free
Voice & Gesture Input Controls	Provide a large range of interactions natural to humans. System interpretation and of multiple-modality input may be difficult; success depends on efficient, effective integration and delivery strategies.

Figure 2-12 - Multimodal displays and controls (Chen et al, 2007)

Apart from speech and gesture interface, brain-computer interfaces have also been used in human-robot interaction research. For example, Esfahani and Sundararajan (2010) have used electroencephalogram (EEG) headset to detect the level of satisfaction of human user, they have reported an accuracy of 79.2% in detecting the human satisfaction level. Zoghbi et al (2009) have measured the affective state of people during human-robot interaction using a hand-held Affective-State reporting device (ASRD). Haptic devices for robot control have seen increased popularity in recent years due its robustness and accuracy in robot motion control (Silva et al, 2009; Vu and Na, 2011). The multi-sensors configuration of mobile device has been utilised in a number of researches for motion control of an industrial robot (Yepes et al, 2013; Lopez et al, 2014). Arumbakkam et al (2010) have developed a multi-modal architecture for human-robot communication of the Honda humanoid robot.

Despite the rich amount of literatures in human-robot interaction in social robot and mobile robot domains (Salter et al, 2006; Goodrich and Schultz, 2007), there has been a lack of research in human-robot interface in industrial applications.

2.7.1 Gesture user-interface

Gestures are important in human cognition and constitute a universal element of human communication across cultures. They also play a significant role in teaching and learning of human (Roth, 2001). Bolt carried out the “Put-That-There” experiment using gesture input back in 1979 (Bolt, 1980). The subject has been extensively studied in various contexts for human-machine interaction due to its expected advantage. Using gesture input, users can experience more natural interaction, because gesture is a natural form of communication for humans which provide an easy-to-learn method of interacting with machines. Some gesture control techniques can offer a more direct interaction with the control subject, because the hand can become the input device in this case without the need for intermediate transducers. Depending on the motion capturing device, the precise position of the user’s body can be tracked and used to define both a command to be executed and its parameter (Baude and Beaudouin-Lafon, 1993). Lidoris et al (2009) have developed the Autonomous City Explorer (ACE), a robot capable to navigate its way through Munich by received directional gestures from pedestrians. Similar gestures have been described in (Thorisson, 1996). Bhuiyan and Picking (2011) have reviewed the history of Gesture controlled user interfaces and identify trends in technology, application and usability. They have reviewed a number of gesture control interfaces developed for research projects and commercial products. It was pointed out that the evolution of gesture based systems has accelerated in the last several years due to improved vision sensing technology. Initially gesture input was limited with the use of wearable motion capture devices such as data gloves. The problem of wearable devices is that it might hinder the user’s movement which causes poor usability and discomfort for prolonged period of usage. Another important aspect is the cost of these motion tracking devices have become more affordable (Bhuiyan and Picking, 2009).

There are many other types of gesture user-interfaces for human-robot interaction. Iba et al (1999) have developed a dynamic gesture recognition system to control a mobile robot using six dynamic gestures. The system is based on a Hidden Markov Models which include a “wait state” to enable rejection of non-related hand gestures, avoiding unintended robot command while wearing the data glove. It is suggested that high-level command of robot activity can be very useful compared to fine direction control. Similarly, Waldherr et al (2000) have used a gesture recognition interface to control a mobile robot in performing clean up tasks. Loper et al (2009) demonstrated a human-robot interface for mobile robot which combine person following, speech input and gesture recognition. An example of a more simplistic approach is (Cipolla and Hollinghurst, 1998), which allows people to point at a target object with their finger to initiate robot pick up routine, and then point at a location for drop off.

2.8 Interaction in proximity

Two of the main concerns when applying robots into unstructured environment populated by humans are safety and dependability (Corke, 1999). The safety aspect of collaborative robot design has been a popular research area in recent years. There are a number of safety strategies in collaborative robotics, for example back-driveable joints and gravity compensation (Brooks, 1983), safer mechanical design (Brooks, 1985), improved actuation/ controller design (Khatib et al, 1985; Kröger, 2011; Parusel et al, 2011) and safe plan planning (Balan and Bone, 2006).

Safe interaction between humans and robots in proximity has been studied in various contexts. Liu et al (2005) have developed a planning method for safe interaction between human arms and robot manipulators based on mapping moving obstacles into Configuration Space. In this research, motion planning in dynamic environments and interaction strategy in task planning were considered simultaneously. The concept was only tested using a simulation model and the authors have left the future work to implement on more precise models. Similarly Hanai et al (2011) have presented a model and motion generation method for the task of collaborative pick and place between a robot and a human. The method has been simulated to confirm the effectiveness of the proposed strategy. The authors stated that applying such a method to a real robot is a major future work, but there are a number of issues to overcome prior to that, which include tracking of the human hand with minimal delay and human trajectories estimation.

Kunz et al (2011) have presented a strategic planning algorithmic model for human-robot interaction with hybrid dynamics. Their model was designed for predicting human motion which allows the robot to select optimal motions in response to human actions and increase safety. For experimental purposes, they implemented their model to simulated human-robot fencing which enabled a 7 dof robot arm to block known attacks in any sequence. Game theoretic tools have also been applied to process action plan for the robot to perform defending actions. This research has shown the potential applications of gaming theories and technologies in robotics.

2.8.1 Safe motion planning

It is accepted that collision avoidance and path planning are valuable functions for a collaborative robot to be equipped with, and therefore this research has investigated existing techniques in this subject area. There are numerous different solutions which have been proposed to the collision avoidance problem, and there are different approaches depending on the specific application (Kroger and Wahl, 2010; Vannoy and Xiao, 2008). A number of reviews have been published by various institutions to compare different methods by their efficiency, complexity, and processing requirements. Reviews such as (Kuchar and Yang, 2000) have evaluated different collision methods which have been applied in automated air traffic conflict detection and resolution (Shim and Sastry, 2007; Tadema and Theunissen, 2008; Lai et al, 2011; Luongo et al, 2010; Drury et al, 2010). A number of relatively simple motion planning strategies have been used in path planning of mobile robots, for example fuzzy-rule-based algorithm (Lee et al, 2011), neural networks based on information fusion technique (Hu, 2009) and terrain reconstruction method (Cai et al, 2005). Some of the algorithms described are highly complex and demand enormous computing power to process in order to minimise delay in the generation of a solution. Artificial Potential Field (APF) is a popular choice of approach documented within collision avoidance research with the advantage of not demanding significant computing power to effectively calculating a safe plan. The method has been further developed and tested in number of research projects which require path planning for manipulators and mobile robots (Warren, 1989; Khatib, 1985; Flacco et al, 2012). Pedrocchi et al (2013) have developed and tested a robot collision avoidance system with safety for human and robot collaboration as the emphasis. They have pointed out the safety options provided by the basic supply of industrial robots are still limited which hinder the possibilities of safe design of collaborative system. It was also mentioned that collision avoidance-based motion planning requires a significant amount of sensor data exchange over the network which introduces architecture issues in terms of information flow, protocols and transmission performance. A safe network has been created which involves a number of non-safety rated sensors and computers for processing algorithms and cross checking data to fulfil the requirements of IEC61508. Their paper describes a Finite State Machine (FSM) approach with three super-states. The three super-states include safe, warning and danger areas which the collision avoidance will only be activate in the warning area. Kulic and Croft (2005, 2006, 2007) have developed a safe planner which minimises the danger criterion during the planning stage ensures that the robot is in a low inertia configuration in the case of an unanticipated collision, as well as reducing the chance of a collision by extending the robot centre of mass from the user. It is reported that participants felt less anxiety and surprise with their safe planner when compared to a conventional potential field planner.

A collision avoidance function will not be developed in this project for a number of reasons. Firstly, the development and testing of a safe collision avoidance system requires a significant amount of resources which is out of the project scope. Secondly, as explained in (Pedrocchi et al, 2013) the execution of safe collision avoidance algorithms wholly relies on measurements from sensors that return obstacles' positions and motion, but sensors currently available for such development are non-safety rated. Furthermore, collision avoidance may clash or introduce restrictions on other functions of the system. For example, the gesture control input is designed to allow an operator to alter the robot position when required. In some cases the operator may be required to be positioned within the robot's warning area for observation purposes. At this point the robot speed can be reduced to enable the gesture control to safely continue. However, the presence of a collision avoidance system will prohibit this to take place. Moreover, collision avoidance will create a significant amount of data flow which may increase the latency within the system.

2.9 Robot Safety

Automation has provided many benefits in numerous applications area, but it has also introduced new problems that have resulted in accidents. Several highly publicised incidents have demonstrated that automation system can introduce new vulnerabilities in system performance by overly dependent on human capabilities and limitations when designers introduce automation from a purely technology-centred perspective (Billings, 1997; Parasuraman and Byrne, 2003). Human and robot coexist in the same workspace can introduce additional safety risks when compare to fully automated system guarded within a cage. Matthias et al (2011) have discussed viable approaches to risk assessment for collaborative robots and potentially effective future methodology to resolve the relevant low-level injury risks.

The workspaces of industrial robots are traditionally isolated from human using safeguard such as fence with locked safety doors or light barriers (BSI, 1997). A combination of improving technology and changing regulations has the potential to allow closer interaction between human operators and robotic equipment (Zanchettin et al 2016). Improving sensor technologies, combined with high speed computer processing, could allow the real time monitoring of the environment around automated equipment and thus remove the need for fixed guarding (Jeong et al, 2016; Vogel et al, 2016), the current market capability of robot safety monitoring devices is described in appendix A2. According to the safety requirements for industrial robots EN ISO 10218-2: 2011, it is important to maintain a safe separation distance between the human and the robot in a dynamic manner. This distance can be calculated using the safe distance formula provided by the standard of safety of machinery EN ISO 13855:2010. The formula is illustrated as follows:

$S = K \times (t1 + t2) + c$

Each symbol represents the follows:

- t1=Response time of the protective device itself
- t2 = Response time of the machine
- C = Potential approach towards a danger zone undetected by the protective device
- K = Anticipated approach speed of the human body or parts of the human body
- S = Safety distance

The current robot safety standards have undoubtedly induced some limitation in the collaboration between human and robot. To design a robot cell which fulfils the current safety standard, a robot with long reach and high speed capability would be inefficient to use in tasks which involve frequent human interaction, because the safeguarding would be required to be setup to separate human from a great distance to the robot during its operation. For the ease of setting up and for safety reasons, a small robot is used for development of this project.

2.10 Robotic sensing

The system requires sensing capability to support the tracking of human within the robot’s work space, and therefore a sensing device is needed for the system. Literature reviews have shown there are a number of types of sensing devices which has been used in relevant research areas which include localisation, gesture/voice input, and object detection. There are two main types of sensors which are contact and non-contact. Most contact type sensors used in robotics include force sensor, torque sensor, and tactile sensor (Mittendorfer and Cheng, 2011; Fritzsche et al, 2016). The Universal Robot UR5 robot described previously is embedded with a number of torque sensors at its joints, and these sensors provide the signal that are required for the post-collision safety function. However, the aim of this project is to develop a system with contactless input, and therefore a non-contact based sensor is required.

2.10.1 Non-contact sensors

There are 2 types of non-contact sensing which are passive and active. Sonar sensor detects object using sound in an active manner, where it emits pulses of sounds and listens for echoes. It is commonly used in mobile robots for navigation, but it is poor for detection of complex shape so making distinction of human and non-human will be difficult. Sonar sensor has been largely replaced by radar, which is more robust and less affected by environmental conditions. Laser Radar has been broadly deployed in military and mobile robot applications. It is effective for long distance motion measurement and they can operate through adverse outdoor condition. The state of the art of laser radar can be used for 3D image and video reproduction. However, producing and processing of high resolution 3D radar image require substantial computational processing power, and 3D laser radars/scanners are generally very expensive. Therefore the overall system cost will be significant, so it is not suitable for achieving the objective of developing a relatively low cost system.

There are a number of movement based sensors which include sensitive skin, RFID, and whisker. Sensitive skin and whisker technology have been used in robotics for navigation and human interaction of small humanoids and mobile robots, but they are only effective when the object is within a very short distance to the sensor, so they are not suitable for the application of this project which involves large working area. The sensor should provide sufficient amount of time for the robot and the processing unit to react to the situation, so that a new trajectory can be generated for the robot to avoid the collision. A 3D tag-based RFID system has been demonstrated in previous research (Roh et al, 2009) to perform object recognition as well as determining orientation and location of the object. The RFID technology can operate from a reasonable range, but the object to be detected requires having a number of embedded tags. For a person, they will be required to wear a suit with RFID tags. Therefore, this does not match the system requirement of this project, because the monitoring function should be capable of detecting unexpected intruder of the working area.

Finally, machine vision is currently the most common type of passive robotic sensing and it has been used in a broad range of applications which include measurement, product verification, safety monitoring, quality check, localisation of mobile robot, and gaming. There are various researches which use machine vision for the detection of human presence, and evidences have shown that vision sensor is capable of supporting real-time 3D human tracking.

2.10.2 Vision sensors

It is identified that there are 3 types of 3D vision sensor technology which are applicable for robotic vision, and these include stereoscopic vision, time of flight, and structured light. Each of them has their advantages and disadvantages. Stereoscopic vision is currently the most common 3D sensing method, and it has significant applications in machine vision where accuracy and fast response time are inessential. This approach combines 2 or more passive 2D image sensors which capture the same scene. The cameras are usually positioned in a way that the cameras' optical axes are parallel to each other, which enable range determination uses the disparity in viewpoints between the cameras to measure the distance to the subject of interest. Stereoscopic vision technology can be cost effective for simple applications but it requires high computing power in order to process and analyse 3D data in real time (Aptina Imaging, 2013; Sansoni et al, 2009).

TOF (time of flight) is an active range system which requires an illumination source. It obtains range information by emitting a modulated near-infrared light signal and processing the phase of the received light signal *(Bascetta et al, 2010)*. A typical TOF sensor consists of an array of pixels, where each pixel measures the time delay between the received signal and the sent signal. TOF offers a direct depth data acquisition which requires less computing power when comparing to stereoscopic vision.

Structured light 3D scanning is an active sensing technology which consists of an image sensor and a projection component. This type of system projects a set of patterns onto an object which is captured with an image sensor. The known camera-to-projector separation is used to locate a specific point between them, and the range information is obtained through image processing and triangulation of the acquired data. Structured light technology can be separated into 2 types which include fixed-pattern scanner and programmable-pattern scanner. Both types of structured light scanners project a pattern of infrared laser light on the surface of the object and capture the object using an optical sensor. The main difference between fixed-pattern and programmable-pattern structured light is that the latter require the projection of multiple patterns, and the benefits are the ability to obtain greater depth accuracy and adaptation to environment factors. Structured light technology is a good candidate for the use of robotic vision. It can deliver high level of accuracy with less depth noise in indoor environments.

2.10.3 Microsoft Kinect

All 3 types of vision sensors mentioned have their advantages and disadvantages, and all of them are applicable to the system in this project. After some cost and benefit analysis, it was concluded that the Microsoft Kinect for Windows (figure 2-13 & figure 2-14) structured light 3D sensor will be used for this project due to the low cost, availability and maturity of the technology.

Figure 2-13 - Microsoft Kinect for Windows Camera unit

The invention of the low-cost Microsoft Kinect has been a breakthrough in 3D sensing technology which enables high-resolution depth and visual sensing. The Kinect for Windows sensor consists of an RGB camera, an infrared (IR) emitter and an IR depth sensor, a multi-array microphone, an accelerometer, as well as a 3D human motion capturing algorithm, which enables interactions between users and the machine without any physical contact, the maximum frame rate is up to 30Hz. There are currently software development kits (SDK) available specifically for the Kinect which allows users to create programs using the data captured with the Kinect sensor. One of the benefits of using the Kinect sensor is the availability of its open source libraries, where various human motion capturing algorithms are accessible, and this will enable this research to focus on the development of the system control framework (Microsoft, 2013).

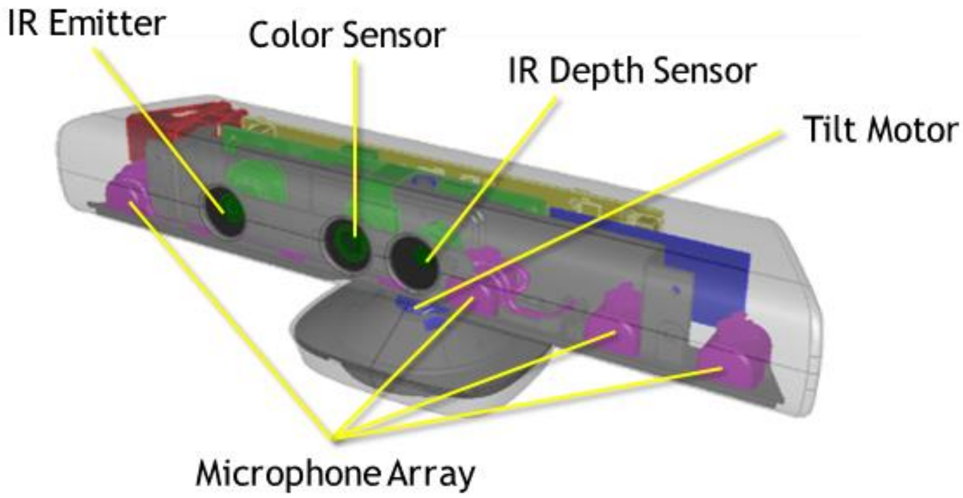


Figure 2-14 - description of the Kinect camera

2.10.4 Leap Motion

The Leap Motion Controller is a low cost consumer hand tracking device designed as a human-computer interface. It is a small device with surface area of 24cm^2 and it is based on stereo vision which has three IR light emitters and two IR cameras (figure 2-15). The field of view of the controller is approximately 150^o and the effective range is approximately 25 to 600mm above the device. The controller is capable to tracking position of hands, fingers, and finger-like tools with sub-millimetre accuracy. The manufacturer claims that the accuracy of fingertip detection is approximately 0.01mm and the frame rate of over 100Hz. This device will be integrated in the system for hand and finger input for robot control during interaction. The capability of the device is further discussed in chapter 3.6.2.

Figure 2-15 - Leap Motion sensor

2.11 Discussion

Industrial robots are proven to be valuable production tools across different industries, but there remain numerous manufacturing processes which cannot be fully automated by industrial robots. Moreover, traditional robot cells are surrounded by hard safeguards which restrict the flexibility of the work cell design and reduce the efficiency of a task. A new breed of industrial robots has been introduced to the market recently. They are known as collaborative robots which can coexist with human operators within the same working space without the requirement of safeguarding, thus new applications of robot are exposed but research is still required to ensure the collaboration can be carried out seamlessly.

It is learned from the literature that safe and flexible human-robot collaboration can maximise productivity and flexibility. There are numerous researches being carried out on developing human-robot interface to improve flexibility of robotic systems, as well as work being conducted on making robot system safer to work with. The efficiency of a production system that consists of both human and robot working together can be significantly affected by the level of autonomy. This particular parameter varies across different system depending on a number of factors such as the complexity of the task, the task flow and scale of the components involved. Thus, the balance should be adjusted by carrying out a cost and benefit analysis to tailor the system. Nonetheless, it suggests that sophisticated interface which enables human guidance of robots' action can be a method to tackle these issues (Few et al, 2006; Brummer et al, 2005).

A number of researches investigated the communication in human-robot collaboration with the aim of improving task performance. For example, Clair and Mataric (2011) developed a communication framework where one of the robot functions supports detection of opportunities to assist in a dynamic environment. On the other hand, Ahmad F et al (2011) attempted to improve a task involving object transfer by perceiving specific part of an object as a signal for exchanging information. It is known that in most human-human collaboration people use speech to communicate with each other, but often one would observes the actions of others to plan their own move without the need of verbal cues. These visual cues can be segregated into three main types and these include gesture, gaze and posture (Goldin-Meadow et al, 2001; Moon et al, 2014; Strabala et al, 2013). Eye gaze and posture are limited to applications in face-to-face interaction due to the nature of these micro movements. In an open working environment these cues can be falsely recognised. Gesture on the other hand, can be coded to specific gesture arrangements which are not ambiguous to other natural movements, thus it can be useful in many cases. This type of human-machine interface has been studied in numerous contexts due to its effectiveness in providing an easy-to-learn method of interacting with machine.

The system should provide an indication of its state to its human user so they can be aware of the robot's action. A typical automated system consists of at least one type of HMI such as a robot teach pendant or touch screen interface, but these interfaces may lack effectiveness in a collaborative environment. The feasibility of robot communication to the user through its motion has been investigated in a number of studies. These include hesitation gestures (Moon et al, 2011), anticipatory motion (Gielniak and Thomaz, 2011) and robot gesture (Ende et al, 2011). The main limitation with these communication methods is robots' kinematics differences to human which can be difficult to represent similar movements by people. Furthermore, these communication motions can interrupt the task being carried out by the robot because the robot has to stop its current activity in order to carry out these motions. In manufacturing terms, they can be classified as non-value added activities which increase process cycle time.

Many of these researches are limited to the social robot domain and it can be difficult to apply the same technology to industrial robots as they do not share the same physical properties or technical attributes. For example, many social robots feature two arms, a torso and a head to anthropomorphise their appearance to improve interaction with humans, whereas industrial robots mostly available in the form of a single robot arm or other complex mechanical structure such as the parallel robot. Furthermore, when designing a system for use in production systems, there are more to consider than just basic functionalities. There are evidences which demonstrate the importance of incorporating a human-centred design approach when the design process involves an automated system (Billings, 1996; Lee and Seppelt, 2009). This is particular important when the design concerns an industrial system, because the developed system will be used for prolonged period of time by different users. Taking human factor into design consideration can help achieve a system with improved usability. However, this element has been neglected in many current researches that concern human-robot interface development.

The knowledge gap exists in the development of an intuitive HRI specifically for industrial human-robot collaboration. This research addresses this knowledge gap by investigating the development of a communication system for human-robot collaboration in industrial settings. The development process comprises of a number of elements to fulfil the knowledge gap. These include system adaptability for integration with other industrial robots, human factor and ergonomic considerations across different design phases, and system practicality in real applications.

3 Methodology

3.1 Introduction

This chapter presents the methodology used to achieve the objectives of this thesis. This entails problem identification, description of human-robot collaborative system, hardware selection and system development. The system connectivity architecture and system components are also described in this chapter.

3.2 Problem Identification

The focus of the research is on improving the interface between human and robot in a collaborative system. This subchapter explains the problem identification process used to seek this underlying problem in collaborative system. The first stage of the study is to investigate the problems as illustrated in figure 3-1. In order to identify all the system requirements it is important to first understand the purpose of the system. To explain the definition of Industrial Human-Robot Collaborative System, the five terms forming the description are explained as follows. As the name implies, it is a type of production system consists of robot and human working together in the same workstation.

Industrial – The term industrial refers to the working environment and application domain of the robot system. In this case, an industrial environment means manufacturing lines where a robot can work as an assistant or partner of the human operators.

Human – The human user is usually to describe production operators on a manufacturing line that carry out manual operations and monitor robot operations, but it can also be a production manager who oversees the flowline.

Robot – an industrial robot is to describe an articulated-arm robot with 5-7 degree of freedom which performs manipulations of components in a manufacturing environment, but the robot can also carry out other task such as machining and inspection. Industrial robots are typically classified by their payload capability and maximum reach. They have relatively little intelligence when compared with social or service robot, and perform specific repetitive tasks accurately. The design and integration of robot systems should comply with robot safety standard which include ISO 10218-1:2011 and ISO 10218-2:2011.

Collaboration – in this context, it is the collaboration between human operator(s) and industrial robot to achieve a manufacturing goal. For example, a collaborative system can be used to increase production output by combining the strong points of human and robot.

System – the collaborative system as a whole consists of robot, human, sensors, control software, tooling and user-interface.

Subsequent to system definition, a number of relevant system influential factors were identified from literature review, and they are mapped onto a system context model to create links between factors (Midgley, 1992). This is explained in greater detail in appendix B.

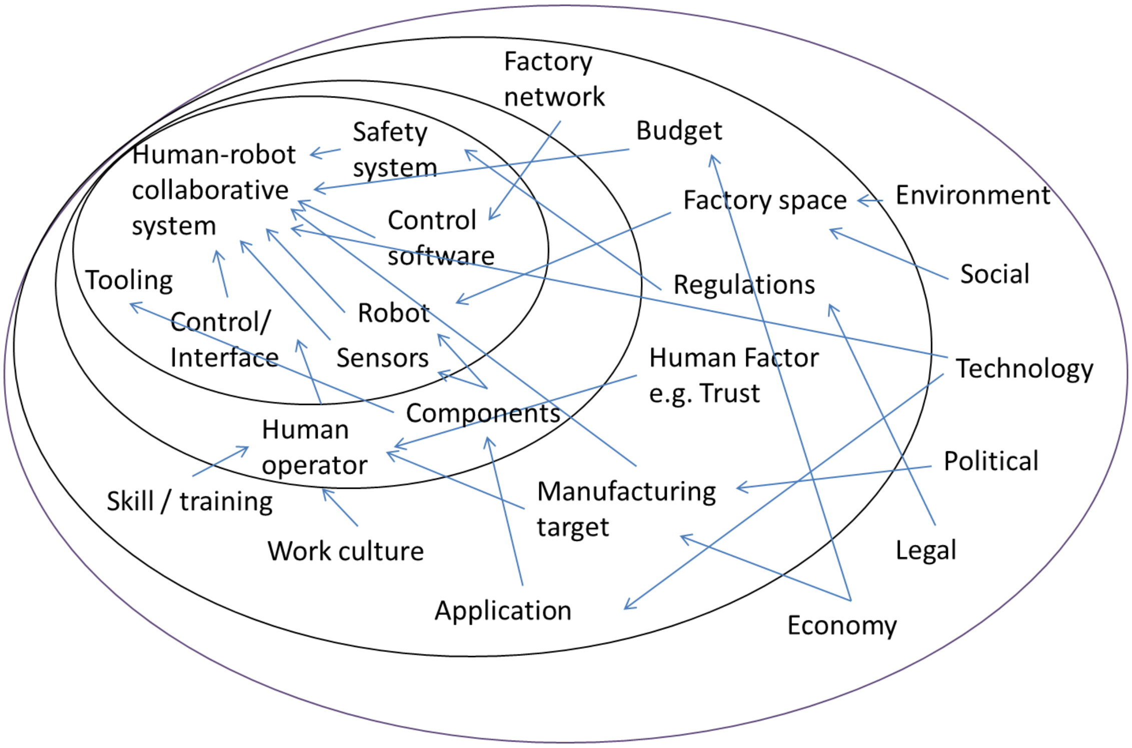


Figure 3-1 - human-robot collaborative system and its influential factors

The system of interest (SoI) in this research is human-robot collaborative system which is located in the centre of the system context model. At the system level, a typical industrial robot cell consists of safety system, robot, control software, user interface, tooling and various sensors. At the wider system level, the human operator can greatly affect the way a collaborative system operates, but a human can only be influenced and not controlled. On the other hand, the components in a manufacturing process can necessitate a major physical alteration in the robot system. For example, the components may carry certain degree of variability which is difficult to automate and require human input. On the environmental level, a number of factors can indirectly affect those in the system, and these include budget, factory space, human factor, regulations, manufacturing target, application, work culture and skills. Altering the system would have no influence or control over these environment factors, but the design of the system can be hindered by some of these factors, for example safety regulations dictate the necessity of a safety setup as well as the type of robot being used. The wider environment consists of political, economic, social, technological, legal and environmental. These factors do not directly affect the system but they may have some influence on those at the environment level.

According to figure 3-1, those at the wider system level can be influenced by environmental factors and changes made at the system but they are ungovernable elements, and therefore it is decided the appropriate level to address issue in human-robot collaboration is at the system level. Thus, this research focuses on system alteration to improve the overall effectiveness of the system.

In many cases, the main incentive in using a robot system is to improve productivity. Evidence shows that productivity can be affected by communication, whether it is between people or systems (Crandell et al, 2003; Takanaka, 1991; Husain, 2013). Thus, effective communication within a human-robot collaborative system is paramount for seamless operation. In order to analyse the problem at the system level it is crucial to understand the structure of human-robot collaborative systems, the architectural differences between a conventional industrial robot and a human-robot collaborative system are explained as follow.

Based on the Zachman method, the 5W+1H questions were applied at the first stage of the development to specify the system requirements which helps planning the design of the system. These questions are summarised as follows:

Table 3-1 - questions asked at the investigation stage

Question	Purpose
Why - current issue	To specify requirement to solve issue
What - available solution	To find current solution
Where - operation environment	To take environmental factors into account
Who - target user	To consider human factor and interaction modes at an early stage
When - timescale of development	To restrict the development to a timescale
How - system capability requirement	To establish system specification

The questions in table 3-1 extract vital information at the investigation stage which aid system design. This is especially important during the first cycle to establish an appropriate baseline to develop the system, but this should be repeated every iteration to identify any advancement in the state of the art. The system requirement should consider technical capability as well as human factor at this very early stage, the complexity of these elements can gradually increase as the development advances. The plan and create phases of the cycle involve mainly design of software and hardware architecture, and subsequently software writing and hardware integration. At evaluation phase, the system should be tested according to the system requirements. For example, a technical capability analysis can be carried out to prove functionalities of system, or a human factor usability study can be used to assess the level of user-friendliness.

3.3 Collaborative robot system

In an industrial robot system, the robot manipulator is the main components in the system which is equipped with an end-effector to perform specific tasks. It is sometimes equipped with external sensors to provide additional system feedbacks e.g. 2D camera to track location and orientation of objects. Many of the state of the art machine vision sensors have on-broad processing unit for data processing such as image recognition, but in most cases a processing computer is still required as the interface between the sensor and the robot.

A human-robot collaborative system has the added element of human operator(s), between the operator and the robot system is a user-interface which enables the two system elements to interact with each other. Figure 3-2 shows a sample layout of industrial collaborative cell, the diagram is based on an illustration extract from a draft standard PD ISO/TS 15066.

There are various types of user-interface, the most common type of user-interface for industrial robot is teach pendant. Teach pendants of industrial robots are usually constructed with hard casing which are IP rated for use in harsh environment. For collaborative robot system, system safety is a requirement to fulfil robot safety regulations unless the robot is designed for direct interaction with a human as described in ISO 10218-2:2011. Factory automation systems usually consist of an indication lighting system to indicate the present of any system errors or machine status, a tower light is a popular device for this purpose but this research seeks to find a more effective alternative to the tower which can reduce reaction time and increase awareness for the user.

Industrial human-robot collaboration is still in its early stages and common design methods, operational models and standards have yet to be established (Ferketic et al, 2006). For instance, the Collaborative robots standard PD ISO/TS 15066 was still in its drafting stage while this research is being conducted. Many interaction techniques are application or task specific, and there is potentially a broad range of human-robot collaborative applications in manufacturing domain which hinders standardisation.

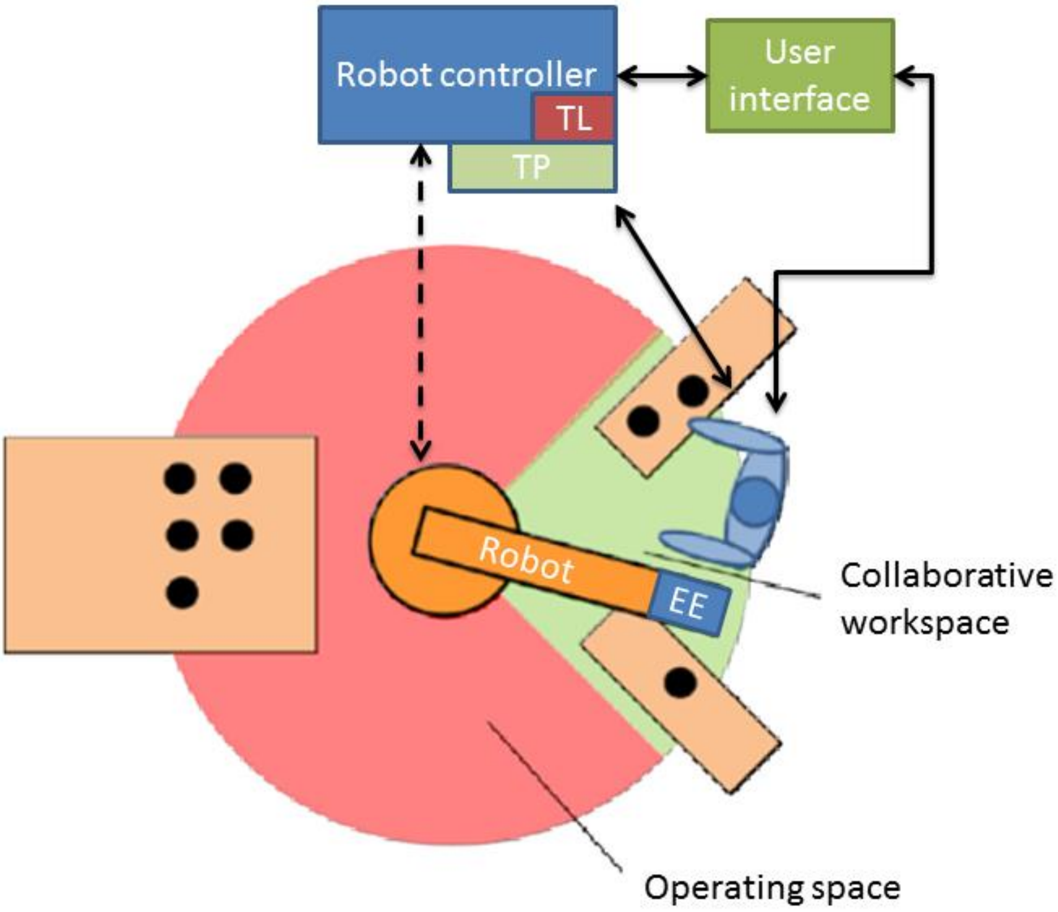


Figure 3-2 – An industrial collaborative environment: TL= Tower light, TP= Teach Pendant, EE= End-effector

3.3.1 User

The human user should be understood as a system element in a collaborative system. It is important to identify the variation of this element in order to design the interface appropriately. Scholtz (2002) has proposed an interaction model which describes different roles in human-robot interaction for mobile robots. This thesis adopts some of the relevant roles and interprets their interaction modes in the industrial HRC context.

The **supervisor**’s responsibilities are to monitoring and controlling the overall situation (for instance, a portion of manufacturing line with multiple collaborative work cells). In this case, the supervisor could be monitoring a number of robots while evaluating the performance based on manufacturing target. Digitalisation has continued to increase in the manufacturing industry which means that future collaborative workstation could be controlled through a central planning system. In this case, the supervisor can communicate with the system to specify an action or modify plans.

The **operator** typical works in a single workstation throughout a shift and has the most frequent interaction and collaboration with robots. Their role is to monitor the robot and ensure the robot is operating as normal, but they could be working on a manual task simultaneously. The robot can reach a point where it is unable to autonomously resolve an uncertain situation whether it is caused by the component or the environment, at this point the operator should intervene and provide guidance to the robot. This interaction is illustrated in figure 3-2.

The **technician** is a skilled personnel who has knowledges such as robot programming languages and mechanical skills. The technician could interact with a robot at the physical level as level as programming level using tradition HRI such as teach pendant and off-line programming.

The **bystander** could be anyone in the surrounding area of the collaborative work cell. They are not responsible for monitoring or have any interaction with the robot, but they could be a factor in altering the robot’s action. For example, a bystander can accidentally walk into the operating space (figure 3-2) and causes the robot to stop.

The characteristics of different roles are summarised in table 3-2:

Table 3-2 - Roles in HRC and their characteristics

Role	Characteristics
Supervisor	Monitor and control the overall situation

	Could be monitoring multiple robots
	Communicate with robot to specify an action or modify plans
Operator	Frequent interaction with the robot
	Monitor the robot to ensure normal operation
	Interaction with robot to resolve uncertainty
Technician	Robot programmer
	Mechanical skills
	Capable to interact with robot using conventional HRI
Bystander	Does not interact with a robot directly
	Can alter robot by accident e.g. triggering e-stop

This thesis focuses on the communication between operator and robot, but some of the integrations have also taken supervisor interaction into consideration for comprehensiveness.

3.3.2 Roles of operator

The roles of the operator in a human-robot collaborative system can be further described with regard to three types of activity in the 3-I classification for HRC, these are interaction, intervention and interruption. These activities can be expressed with reference to Annex E of ISO 10281-2:2011:

Interaction – routine activities which involve the operator and the machine working together inside a collaborative workspace to complete a common goal. For example, hand-guided assembly, common assembly and machine service.

Intervention – manual activities being carried out on a regular basis which put machine operations on temporary halt. These activities can include refill and removal of materials, manual inspection, and manual rework. The operator can carry out the work within the collaborative workspace or through an interface window.

Interruption – unexpected events which can cause disruption to both automated and manual process. This type of event can be triggered by other systems outside the collaborative workspace. The operator in this case is responsible for communicating with other systems or to carry out remediation such as programme restart to resume normal activity.

3.4 Hardware selection and Integration

High-level system structure of a human-robot collaborative system has been defined in chapter3.3 and this architecture is used to set the baseline for the hardware selection and integration which support interface development and evaluation in this thesis.

A number of system requirements have been identified, the list of requirements and the purposes of them are summarised in table 3-3:

Table 3-3 - system requirements and their purposes

System requirement	Purpose
Consists of at least one industrial robot manipulator	To carry out manufacturing tasks
Safe for collaboration with human operator in proximity	Compliance to safety standards and ensure the safety of user
Capable of communication with user in a speedy and effective fashion	To enable user to react quickly when intervention is required
Capable of receiving input from user through hand gestures in mid-air	To provide a user-friendly control interface which require minimal training

A number of system requirements have been identified above to lead the hardware selection process. The primary requirement of the system is to have at least one robot manipulator to perform tasks or assist the human operator. In a collaborative system, the safety of the operator is paramount so the developed system must be safe for human and robot to coexist in proximity. In a collaborative working environment, the operator can bring foreign objects into the working area to support their work. In this case, workspace monitoring can be incorporated to avoid collision between the robot and the object. A collaborative robot system can require frequent human intervention to resolve uncertainties and decision making. The robot system should be capability to convey these messages to the user efficiently to minimise robot downtime which can result in losing productivity, thus the developed system should have the capability to catch a user’s attention in a speedy fashion while the user can perceive the correct information.

Traditional teach pendant designs of the last two decades typically consist of an information screen and a high number of buttons for user input as illustrate in figure 3-3. A teach pendant enables the user to programme a robot as well as change settings. The movements of an articulated-arm robot can be controlled by rotation movement at each joint, linear movement in Cartesian and rotation around pre-defined axes. Robots can be programmed to perform repetitive routines using manufacturers’ proprietary programming languages, which is often carried out on a teach pendant or offline programming. However, teach pendants often feature complex button layout and the graphical interface vary between robot manufacturers so significant user training is necessary prior to any operation. In this case, a collaborative robot system should be user-friendly, and while embracing the skill enhancing characteristic, it should enable novice user to interact with without any expert knowledge. Thus, the system should feature an intuitive user-interface which enable user to make commands through simple hand movements.

Figure 3-3 - COMAU industrial robot teach pendant

Based on the system requirements and the system diagram in figure 3-2, a number of system components are identified and illustrated in table 3-4.

Table 3-4 - system components and their purposes

System component	Purpose
Industrial robot arm	To manipulate end-effector to carry out task
Safety system	To ensure safety of user and surroundings
End-effector	To perform specific action
Sensing device	To enable tracking of user
Processing unit	Data processing of sensor data and interface of subsystems
Indication system	Indication of robot status

The Universal Robot UR5 robot has been selected as the manipulator for preliminary development of this system due to its safety rating, acceptable performances and connectivity options. The use of a safety rated robot eliminates the requirement of safety system setup which allow this research to focus on the main project scope. The robot features Joint Torque Limiter mechanism which enables the robot to stop immediately in the event of a collision to minimise damage to its surroundings. This particular feature enables user-interface development to be carried out more safely and efficiently. However, the final goal of this work is to develop HRI control system for conventional industrial robot with medium to high payload capability. Unlike small payload collaborative robot, medium to large industrial robot can incur significant damage if collide with surrounding objects or people, so the integration of gesture interface shall be carried out with caution. The capability of gesture control of an industrial robot is demonstrated using a COMAU NM-45 industrial robot with 45kg payload and approximately 2m reach.

A Schunk pneumatic gripper has been chosen as the default end-effector for its simplicity to setup and flexibility for fingers configuration. The gripper is used to demonstrate actuation capability of the developed user-interface as well as to carry out pick and place in experiment.

One of the system requirements is the capability to receive gesture input from user using contactless device, thus sensors are required for tracking of people. It was identified that the Microsoft Kinect and Leap Motion are designed to track user’s body movement and hands’ movement respectively. These devices feature software developer toolkit which can be used to develop software for processing these sensor data, and therefore they are selected for the sensing of the system. The functionalities of these devices are discussed in more detail in chapter 3.6. A processing computer is required for the interface between the human tracking sensors and the robot controller. To validate the compatibility of developed software, they have been tested on various lab computers with MS Windows interface.

3.4.1 Connectivity

The robot is powered by the robot control through a dedicated power supply cable. The operation of the gripper is driven by the main air supply of the laboratory where the main air supply is routed to a 2-way pneumatic valve system which is controlled by the I/O output of the robot controller. Each valve controls either the open or close operation of the gripper. The robot system is connected to the processing computer through TCP/IP network, which receives control information from the operator through the sensing device. The processing unit in this case operates as a system central control between the robot and the human operator, which incorporates programmes for various processing and communication. The sensing devices continuously obtains user tracking data within its own working area, and the processing unit receives the data, analyses the image and performs human recognition and tracking. The sensing device is connected to the computer via USB connection. The tracking data will be processed by an appropriate programme, which will pass control information onto interface software which translates this data into comprehensible commands for the robot. This information is sent to the robot controller via the TCP network at a rate of >10Hz. This will enable the robot to react to the user's intend accordingly. A schematic of the system can be seen in figure 3-4. The developed indication system communicate with the robot system through I/O control, the change in signalling is made based on the control input of from the robot controller and the relative position of the user which is explained in more detail in chapter5.

3.5 System development

The developed system is a human-robot interface system which accepts gesture commands from the user. The development has been carried out on a collaborative robot system with vision sensing capability which supports contactless input from human operator within the work cell. The system was evaluated for its reliability, practicality and usability. Due to the nature of the system architecture where a human is part of the system loop, it is sensible to consider the development with human-centred design method in which human factor considerations are taken into account in a prospective manner to outline feasible design options *(Kidd, 1992)*. The major system development activities consider two subsystems (figure 3-4). Subsystem1 is the control interface, responsible to process command from human operator and interface with the robot system. Subsystem2 is the indication system which indicates robot status to the user(s). A base system was integrated to support the development in system 1 which consist of sensors, central control system and interfaces. The work carried out on subsystem 2 were mostly exploratory and experimental base due to the lack of literature.

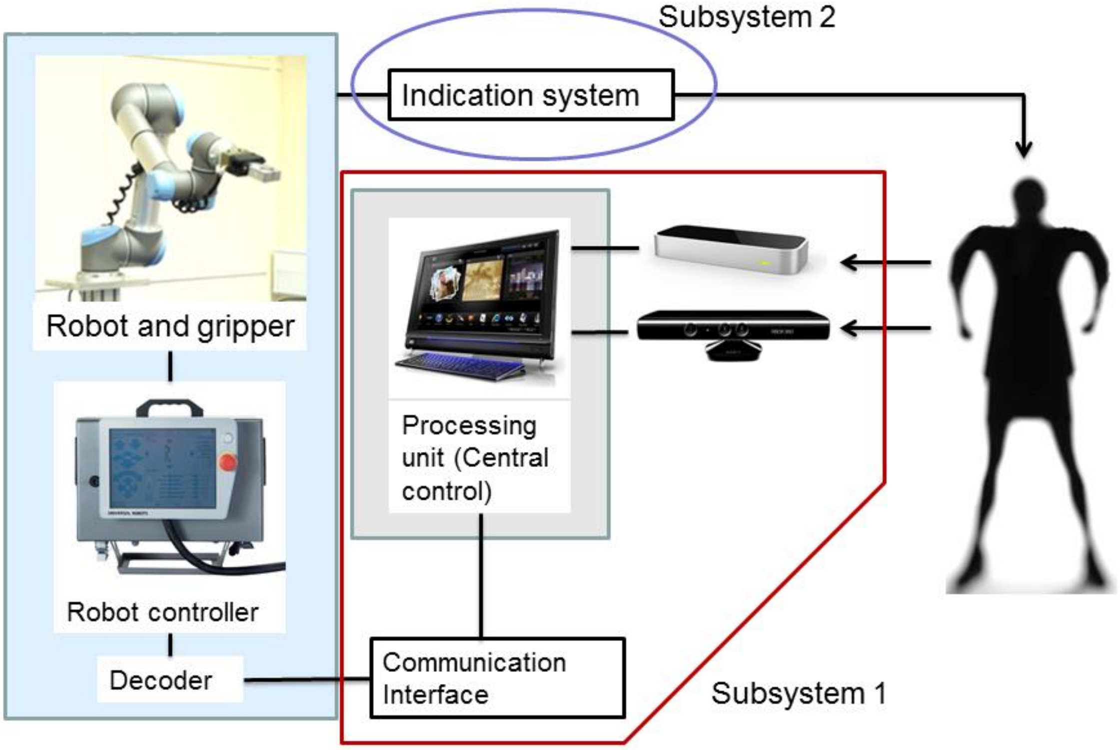


Figure 3-4 - illustration of subsystems

3.6 Human recognition and tracking

It was identified at the beginning of this PhD that Microsoft Kinect and Leap Motion were two of the most suitable devices on the market at the time to use for gesture input. Both devices are consumer product aimed at gaming and computing market which can be purchased at a relatively low cost compared to industrial 3D sensors. These products feature software developer toolkits for use with these devices to enable tracking of hands and other body parts. Both sensors were deployed in the initial development cycle of this research because the two sensors have different characteristic, the Microsoft Kinect is useful for full body tracking at mid-range and the Leap Motion is good for hand tracking at close-range. Their capabilities and applications are described in the following sub-chapters.

3.6.1 Body and hand tracking

The Kinect can track up to 20 joints using its standard Software Developer Toolkit (SDK hereafter) at a range of 800mm to 4000mm from the sensor (figure 3-5). A number of researches have been carried out to investigate the performance and application of the Kinect device (Han et al, 2013). Khoshelham and Elberink (2012) has investigated the accuracy of the depth data and concluded that the Kinect depth measurement is less accurate with increasing distance from the sensor and reaches error of 4cm at the maximum range. However, Ballester and Pheatt (2013) have concluded that although the device has limitations with respect to spatial and temporal resolution, overall the Kinect has been found to be an effective device with the potential for high speed data acquisition in many applications. Furthermore, Obdrzalek et al (2012) have carried out extensive testing on the accuracy and robustness of Kinect Pose Estimation using the official Kinect SDK. It was found that the Kinect skeleton tracking can struggle with occluding body parts or objects in the scene and the variability of the pose estimation is up to approximately 10cm, but nonetheless it has significant potential as a low-cost alternative for real-time motion capture and body tracking. The Kinect for Windows was chosen for this project for image acquisition primarily due to the human tracking capability and its SDK support multiple programming language which enable the developed software to be written using high-level programming language such as C#. For demonstration purposes, the Kinect is attached on a static horizontal surface where the users stand approximately 2 metre away from the front of the sensor. The official Microsoft Kinect driver and SDK are used to support tracking of user because it is part of the off-the-shelf product, which fulfil one of the emphases of this research which is to integrate off-the-shelf devices from the current market. The skeleton tracking data is used in both SPR and DHMT. The Kinect Interaction API is used to support basic gesture recognition which includes open and close hand.

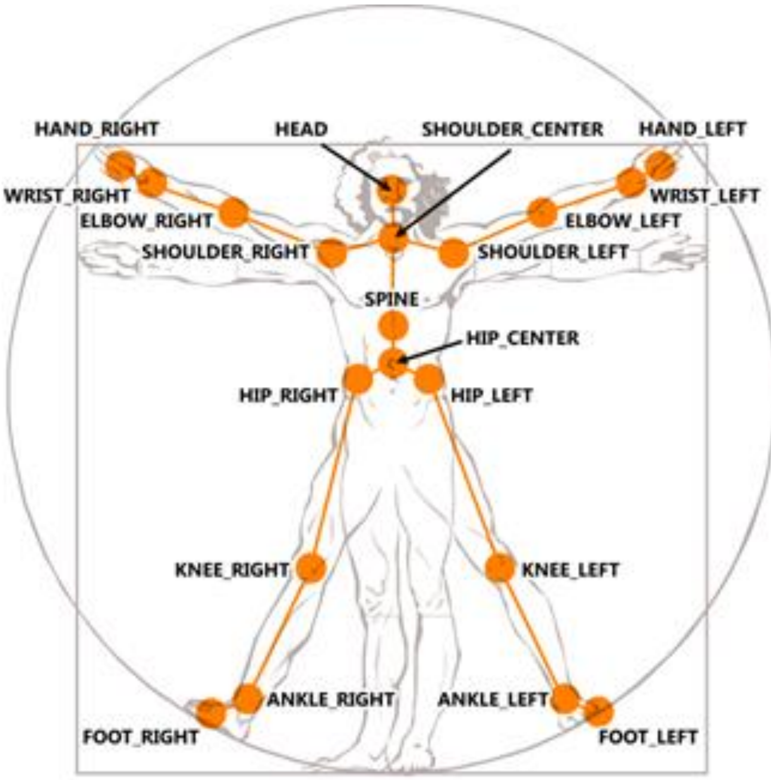


Figure 3-5 - Kinect skeleton tracking diagram (Microsoft)

3.6.2 Hand and finger tracking

The Leap Motion Controller is a low cost consumer hand tracking device designed as a human-computer interface (figure 3-6). Further to the basic specification discussed in chapter 2.10.4, the manufacturer claims that the accuracy of fingertip detection is approximately 0.01mm and the frame rate is up to 300fps. However, Weichert et al (2013) have performed a series of tests to measure Leap Motion’s accuracy using a pen mounted on an industrial robot. The robot was used to manipulate the pen to a series of predefined positions and paths. Using this method, the Leap Motion pen tip tracking data were compared against a set of reference data. They have discovered different results as the manufacturer has stated. It is summarised that it is not possible to achieve the claimed accuracy of 0.01mm under real condition, but the overall average accuracy of 0.7mm from the experiments is still relatively good for gesture-based user interfaces. On the other hand, Guna et al (2014) have performed a series of test on the Leap Motion with the aid of a fast and high-accuracy motion tracking system, and by measuring a static plastic arm with a pointing finger they have measured accuracy with a standard deviation of 0.5mm and best case at less than 0.01mm. However, they found a significant increase in the standard deviation when moving towards the edge of the controller’s working area. Furthermore, the set of measurements in the dynamic scenario have revealed some inconsistent performance of the controller which is limited by its inconsistent sampling frequency. Nonetheless, the Leap Motion can measure hands positional data which cannot be done with other markerless and non-contact off-the-shelf device so it is an alternative sensor to be used in this system. The weaknesses of this particular sensor can be compensated by taking appropriate measure during the development of the gesture control.

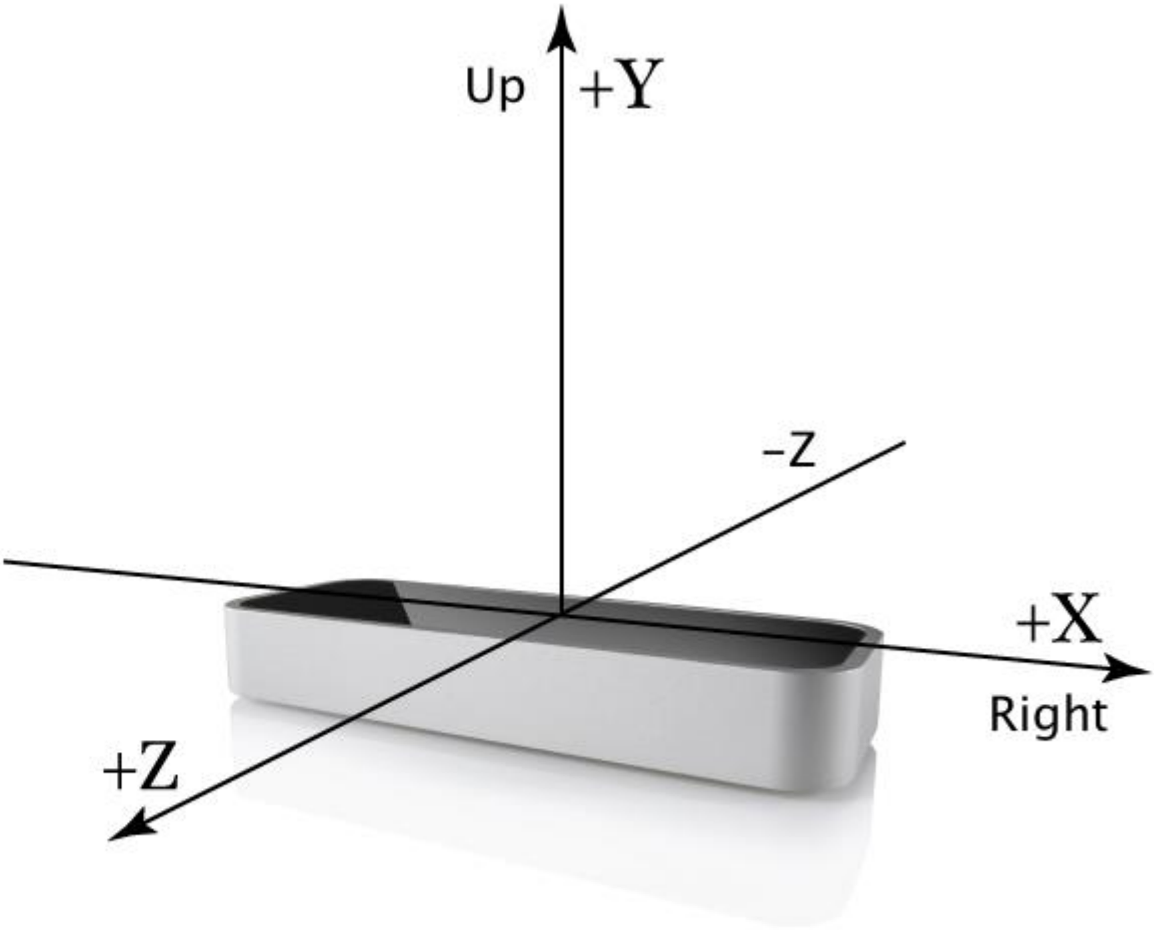


Figure 3-6 - Leap Motion Controller and its working frame

3.7 Central control

The developed system layout has been described previously and it is illustrated in figure 3-4. The processing unit acts as a central control of the user-interface which receives input from the sensors and produces control output for the robot. The unit is a PC computer which consists of a Central Control Programme (CCP) which is embedded with various SDKs to received input from different sensors (figure 3-7). The programme was developed as part of the research. A number of human recognition and positional tracking algorithms will be used within the Kinect SDK toolkit and Leap Motion API, and the positional data is constantly transferring onto the CCP during operations. The CCP is capable of translating human user’s intentions into robot control signal.

The CCP is created using the C# programming language. The C# language is selected based on its compatibility with both the Kinect and Leap Motion drivers. It is also relatively simple to use when compared to older language such as C++.

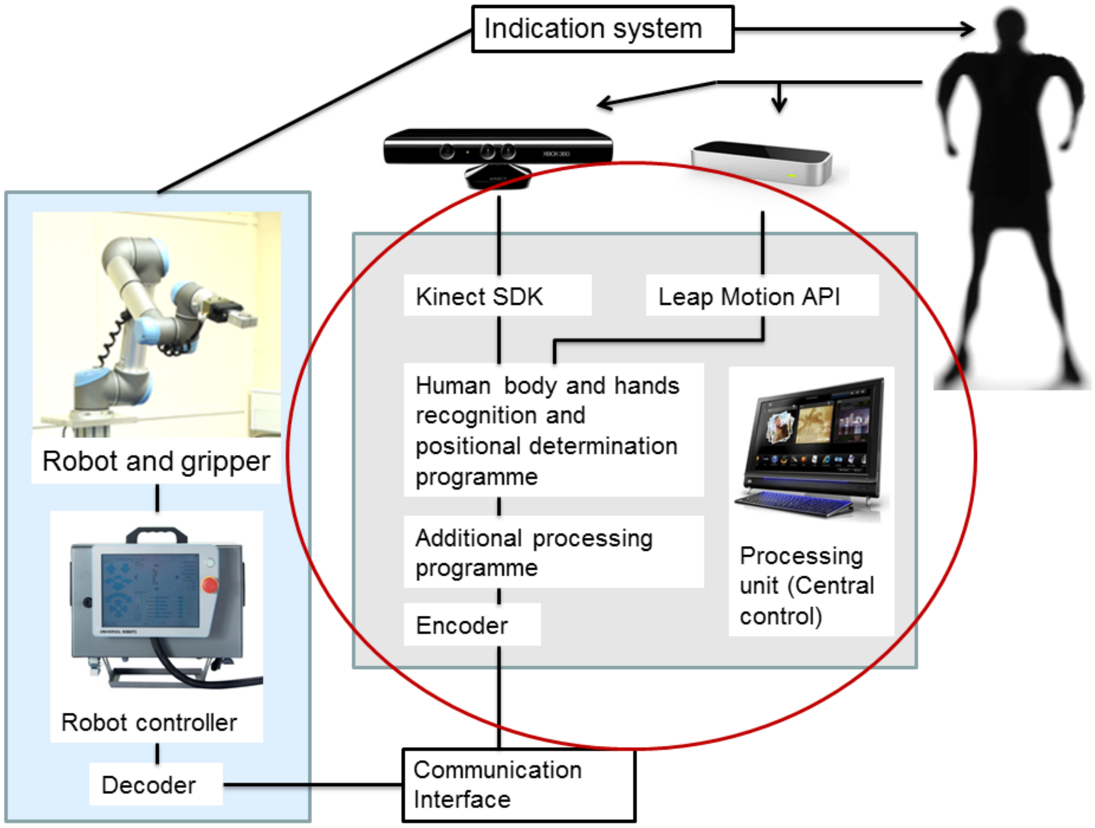


Figure 3-7 - a breakdown of the CCP programme

The communication between the control unit and the robot must be effective for the robot to respond to any situations with minimal delay. Two control frameworks with different commanding methods of the robot have been proposed. Both methods involve the control interface making decisions based on the user's relative position and hand gestures. Once a decision has been made, the control interface will send a signal to the robot to execute an action. The first method communicates with the robot via Ethernet through the robot's real-time communication port (figure 3-8). In this case, the robot is the server and the control unit is the client. The control unit commands the robot by sending lines of script code, which is the proprietary language used by the robot controller. The robot will execute the command immediately once it is sent. The drawback of this method is the disruption of the robot's current movement, because the robot controller will prioritise any input from the real-time communication port. Therefore, it is not suitable for running an offline program which has been stored in the robot controller and the control interface simultaneously.

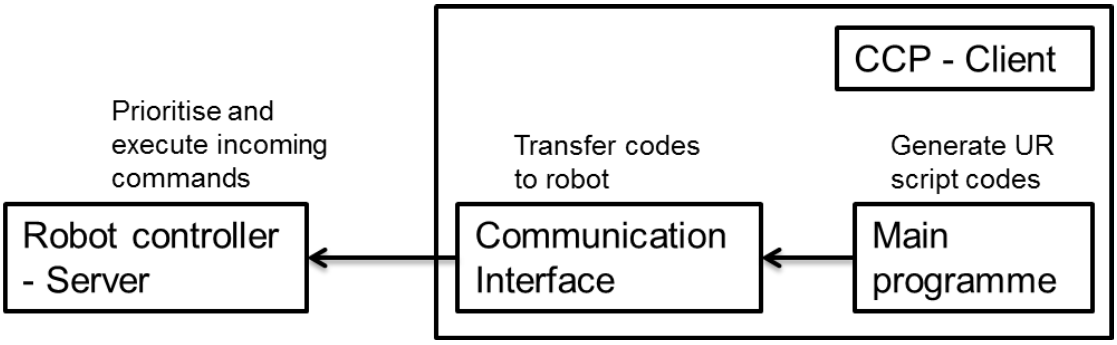


Figure 3-8 - CCP operates as the client sending script code to control robot

The second method also uses Ethernet as a mean of communication, but the role of the control unit is reversed from the previous method. In this instance, the control unit operates as a server and the robot is a client (figure 3-9). A program containing a number of threads is stored on the robot controller, and these threads run concurrently with each other. One of these threads contains a program which receives variables from the server (control unit), while others will contain movement and action sequences. The action sequences are assigned with variables or number, which can be called by the control unit. The second method enables the control unit to pause the robot's current movement to perform action, and then resume normally afterwards without any major disruptions or trigger of the emergency stop. Furthermore, this method is more adaptable when compared with the first method because the control data can be encoded as predefined variables which can be decoded by a robot programme. Thus, robot decoder programmes can be written for different robots to receive commands from the same control interface. Due to the adaptability, the second arrangement is selected for the interface between control system and robot.

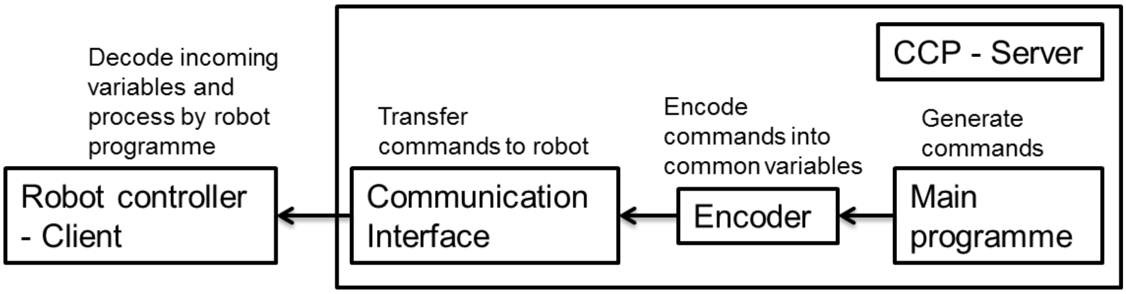


Figure 3-9 - CCP operates as server sending encoded variables to robot

3.8 Robot decoder programme

Chapter 3.7 explained the schematic of subsystem communication and the client-server model used in this thesis. The robot controller (client) receives predefined variables from the control system (server), and the decoder programme within the robot could interpret these signals and prompt appropriate action. Depending on the structure and application of the robot programme, the decoder programme can be integrated into the main robot program. Some robot controllers support multi-thread programming, but many robot controllers are restricted to serial programming which can affect the flexibility of the integration.

Figure 3-10 illustrates two generic models for multi-thread programming and serial programming. For multi-thread programming, the interface programme module can be working in a dedicated thread and override the main routine only when required. The transition between automatic mode and manual control should be carried out smoothly, and the architecture must be designed carefully to avoid unforeseeable disruption to the operation. This type of programmes enable the robot to respond to manual command more promptly when compared to serial programme. However, many industrial robot controllers only support execution of a single thread at a time. In this case, the interface module must integrate sequentially to the main robot routine. It is demonstrated in figure 3-10 that the main routine can be separated into smaller segments where the interface can fit in between to check for incoming signals. For example, in a manipulation task an operator can use gesture control to run an industrial robot by activating pre-programmed routines to carry out a series of movements.

Nevertheless, the functionality of a robot programme can vary significantly depending on the task. This thesis demonstrates the integration of gesture control interface in both programming applications.

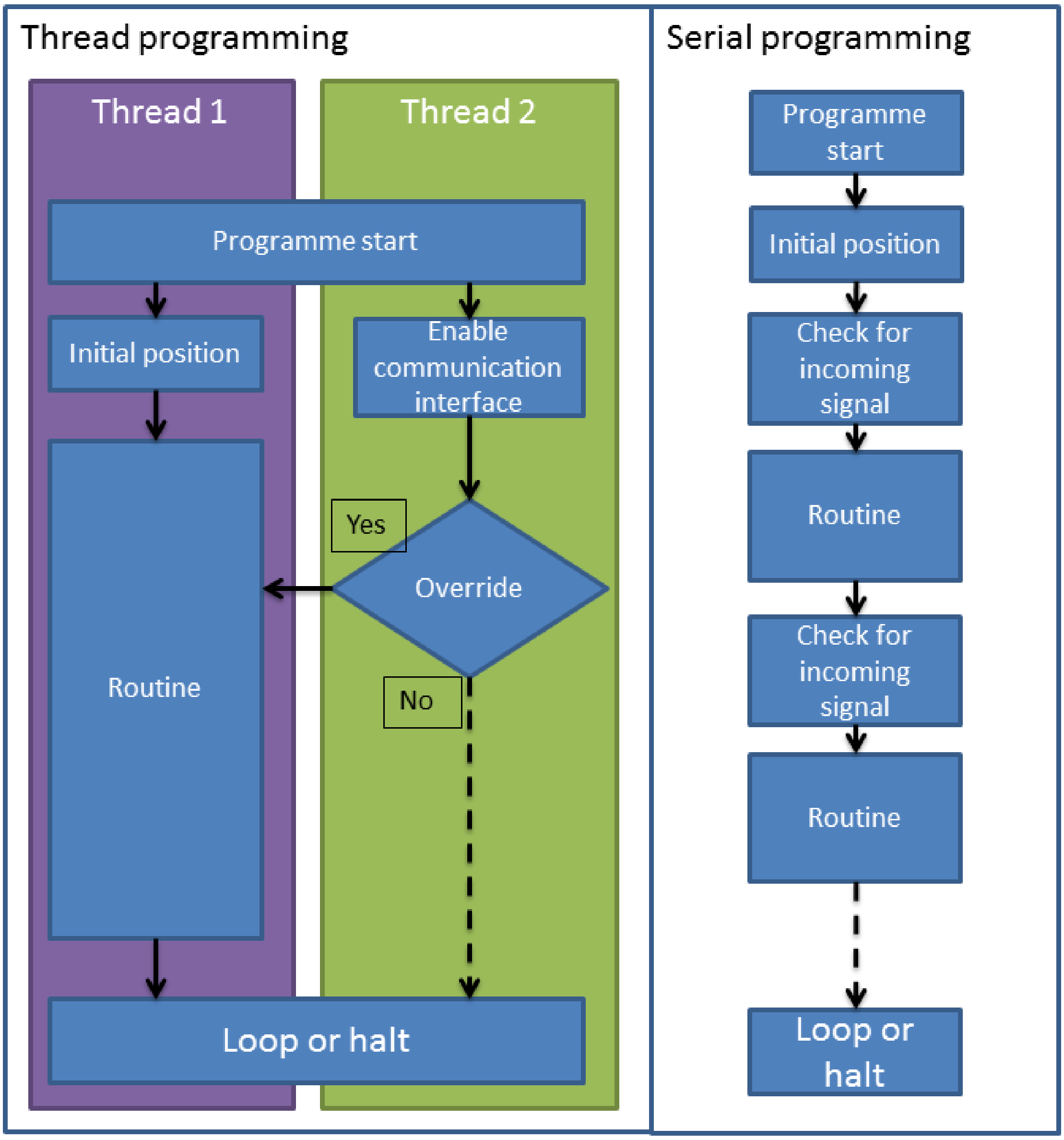


Figure 3-10 - robot thread programming and serial programming

4 The development of a gesture control system for robot interaction

This chapter describes the system development process of a gesture control user-interface for use in industrial collaborative system.

4.1 Introduction

True human and robot collaboration involves a high level of cooperation, and therefore an effective method of communication is crucial for the overall efficiency of such processes (Green et al, 2008). In human to human interaction, voice and hand gestures are practically inseparable, hand gestures are used to strengthen the speaker’s ideas, and people sometimes communicate only through hand gestures (Cerlinca et al, 2013). In industrial terms, gesture communication is sometimes preferred due to the nature of operation environments, for example high background noise and communication over a long distance may limit the effectiveness of speech communication (Barattini et al, 2012). For example hand gestures are commonly used in building sites where site workers communicate with crane operator using purely hand gestures. Thus, it is apparent that gesture control could be an ideal candidate for robot user-interface due to its intuitive nature.

4.2 Background

In a traditional factory setting, industrial robots are programmed to operate automatically to perform various tasks in a repeatable and synchronised manner sometime with a number of other robots. In this case, contact type interfaces such as teach pendants and touchscreen human-machine interfaces are used as the primary interface between human and robot, but these devices feature complex layout to accommodate a comprehensive range of functionalities. These devices can require uncomfortable hand and arm motion for tele-operation tasks, which increase workload and also require trained users. This may be acceptable for occasional and short term usage, but for frequent intervention in human-robot collaboration a more effective user-interface is required. In recent years, researchers have been investigating the use of alternative methods for interfacing between human and robot which is particularly common in the social robot domain. User input through hand gesture is a popular idea due to its intuitiveness and potentials. Gesture input can be interfaced using contact type controls such as data gloves which track the user's hand position in real-time in order to enable tele-operation via natural hand movements. However, it has been reported that data gloves hinder the user's movement and are uncomfortable to wear. Furthermore, the use of wearable devices is often restricted in industrial context because data gloves and motion capture suit often require calibration prior to use which significantly increase man hour of the process, wearable devices may also require frequent maintenance due to wear and tear which increases cost. A vision based system has a non-contact nature which means it is non-invasive to the user's movement and the process involved (Kofman et al, 2005). Furthermore, the state of the art of vision based systems can support tracking of human body position which enables gesture commands or input by body movements.

A number of researches have been conducted on robot teleoperation using contactless human tracking. These control techniques are mainly divided into two types which include the imitation of human natural movement gestures (Nguyen and Perderau, 2011; Stanton et al, 2012; Du et al, 2010) and gesture recognition (Yanik et al, 2012; Wan et al, 2012; Parkale, 2012; Kornuta and Zielinski, 2011). There are standardised industrial hand signals used in crane operation which offer a full range of directional control, such as "up", "down", Left", "Right", Forward", and "backward". Thus, it is possible that an articulated robot can be controlled in Cartesian 3D space using these commands. These gestures are easy to learn and they are widely used in current industrial applications. Moreover, some factory personnel may have already learnt these gestures which reduce training requirement. Robust gesture recognition for robot movement control can be highly valuable in industrial human and robot cooperation, especially in a case when a process recovery is needed. For example, a robot was to carry out a large scale assembly task, but the two components are out of alignment due to misplacement. In this case, a robot operator could use gestures to guide the robot into the correct position to allow the task to continue without the need for a skilled programmer and teach pendant.

Furthermore, gesture recognition offers benefits such as contactless control for robot activation and deactivation, as well as restart after a robot protective stop using gesture command, because activation using a robot teach pendant can increase workload on the operator and requires a specific skill set. (Bhurane and Talbar, 2011) have presented a face and gesture recognition system for robot user authentication. The user is verified using real dual-tree discrete wavelet transform based face recognition, then the authenticated user is further allowed to control the robot using hand gesture recognition. The gesture set is consisted of five basic gestures which are based on finger count. This thesis proposes the novel approach to combine gesture recognition and dynamic hand motion tracking gesture control with face recognition to demonstrate potential applications in the industry.

Despite significant research efforts in technological development of gesture control for robots, there has been a lack of ergonomic consideration in these development processes which may have implications on the users’ health and user experience for long term use. A number of researches have demonstrated that gestures if not designed with human factor can cause muscle fatigue after prolonged usage (Gope, 2011). For example, Beurden et al (2011) have developed a gesture-based interaction technology for interacting with three-dimensional displays for working distance within arms’ reach with the aim to develop a system that is intuitive to use, but their user evaluation has shown that users reported moderate to somewhat strong levels of fatigue in the shoulder and upper arm using the system. This has shown that it is important to not only develop gesture that is intuitive to use, but also include biomechanical constraints of human into design consideration (Nielsen et al, 2003). Norman (2010) has pointed out that a pure gestural system makes it difficult to discover the precise dynamics of execution, but the problem can be overcome by adding conventional interface elements such as menus, operations, tutorials, and other forms of feedback and guides. It was also suggested that because gesturing is a natural, automatic behaviour, the system must be adjusted to avoid false responses to movements that were not intended to be system inputs. It is particularly important in this case because the control object is an industrial robot which has the potential to cause damage to people and surrounding area if it is moving unintendedly. This thesis investigates in the use of existing industrial human factor analysis tool in the development and evaluation of gesture control design. Also, conventional interface design elements are considered in the system design.

It is identified from literatures a number of gesture control methods feasible to use in human-robot interaction. Each method has their merits and flaws so the selection of method should be based on the suitability for the application. As explained previously, a gesture recognition system can be used to command a robot to carry out specific routine or move in a certain manner, a hand following type of gesture control can enable a robot to follow or mimic a person's hand movements. At the initial development cycle, both types of gesture control system were developed to explore their characteristics for an early evaluation and suitability to use for further application. A list of gesture control developments is summarised in table 4-1:

Table 4-1 - a summary of gesture control developments

Control type	**Gesture type**	**Development**	**Characteristics**
Static Pose Recognition	Directive gestures	Virtual Directional Pad	Preliminary development to enable 2D directional control of a robot
Static Pose Recognition	Standardised industrial gestures	Industrial gesture SPR	Recognition a set of gestures based on industrial standardised hand signals using 3D body tracking data
Hand Motion	Natural hand	Dynamic Hand	Enable user to control

Tracking	movement	Motion Tracking (DHMT)	motion path of an industrial robot using hand movement
Static Pose Recognition and Hand Motion Tracking	Standardised industrial gestures and natural hand movement	Integration of SPR and DHMT: a demonstration of application	A system integration of the two gesture control to illustrate potential industrial applications
Static Pose Recognition	Hand and wrist poses	Ergonomic and intuitive robot gesture control	A gesture control system designed using human factor analysis tool to reduce excessive hand arm movement which may increase musculoskeletal injury risk. This system enables user to control an industrial robot in linear motion and movement around different joints.
Static Pose Recognition	Hand and wrist poses	Integration of gesture control with a heavy duty industrial robot	This work demonstrates the methodology of integrating a gesture command interface to an industrial robot, the applications are also discussed.

4.3 Static Pose Recognition (SPR)

4.3.1 Introduction

This thesis investigated in the development of a Static Pose Recognition (SPR) system for industrial robots which includes design and evaluation. Gesture recognition can be classified into two categories: static pose and dynamic gesture. Static poses are defined by the arrangement of a person's body whereas dynamic gestures are marked by the changes in arrangement of a person's body during elapsed time. The advantages of the SPR method include responsiveness, reliability and simplicity for computation. In comparison, a dynamic gesture mostly requires longer time for the recognition algorithms to recognise because it requires observing gesture motion from initiation to completion, for example to complete drawing a circle in mid-air. On the other hand, the SPR method can detect a gesture almost instantly when a matching gesture is identified but gesture design should consider using appropriate techniques to reduce ambiguity which can lead to false triggers.

It is important to consider the system requirements when designing a gesture control system. In this case, the system should be capable of controlling the movement of the robot for event such as system recovery or positional error correction, but also enable the user to make command such as start and stop of routines.

4.3.2 System architecture

The system architecture of the gesture recognition system is illustrated in figure 4-1. The raw data from the sensor are processed by the relevant API which performs the tracking of human body. The tracking data are analysed by the gesture matching algorithms to carry out gesture recognition. Once a gesture is identified, relevant outputs is encoded and then being sent to robot system. The robot programme decodes the variables and proceeds according to the command.

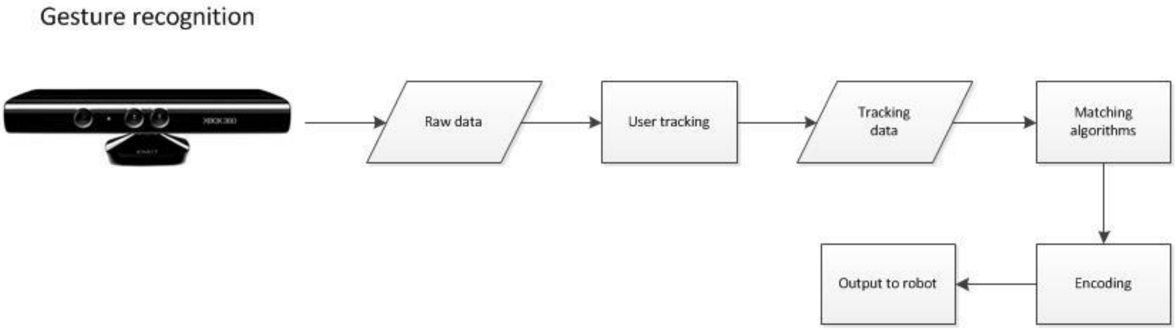


Figure 4-1 - system architecture of the gesture recognition system

4.3.3 Early development – Virtual Directional Pad

The idea of Virtual Directional Pad is based on the directional pad on a gamepad controller commonly used in game technology. The area in front of the user became a Virtual Directional Pad where the user can control the movement of a robot in Cartesian 2D space as illustrated in figure 4-2.

The system tracks the user's movement at a sampling rate of 30Hz using a Microsoft Kinect. For this application, both shoulder joints and both hand joints were being monitored. The Kinect Interaction API was used in monitoring the status of both hands which enable the open and close palm motion to be used as a functional gesture. An algorithm was designed and embedded within the system to measure the Euclidean distance of right hand position (RHx, RHy) relative to the right shoulder joint coordinate (RSx, RSy). Thus, the user could change the direction of robot movement by pointing their hand to a relevant direction on the virtual pad in figure 4-2. The movement control is only enabled when the left palm of the user is closed which minimises false triggers. The open and close motion of the user's right hand can operate the pneumatic gripper. The control system sends control signals to the robot at a rate of 30Hz. The robot reacts to these commands by moving on corresponding axes with 0.25mm increments. Thus, the theoretical resolution of control is 0.25mm (+/- 0.1mm robot repeatability) on both x-axis and y-axis of the robot frame.

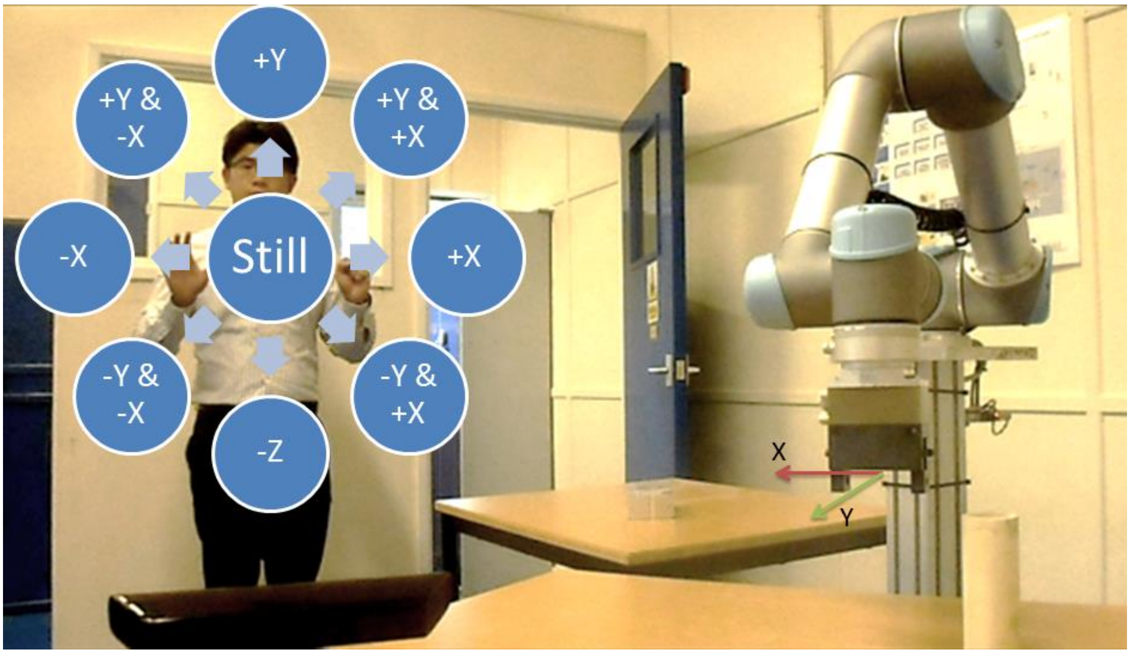


Figure 4-2 - Virtual Control Pad for 2D motion control

A pick and place test was carried out to test the capability of the Virtual Directional Pad in performing a task. It was used to position a robot gripper in the correct position to pick up a cylindrical object and to position the object at the target before the drop. The robot was programmed to stop near the object outside the dartboard area as shown in figure 4-3, at this point the user has to use gesture to guide the robot to position its gripper directly above the object. Once correctly positioned, the user can actuate the pickup routine by closing their right palm. Subsequently the robot moves the object near to the drop off area, the user can use gesture to adjust the position of the object until it reaches the centre of the target dartboard. At this point, opening the right palm actuates the drop off routine which complete the task. This test has been carried out fifteen times by the researcher with full success.

Figure 4-3 - pick and place test using Virtual Directional Pad

A second test was carried out to address more realistic issue in assembly applications. The system was setup to carry out a peg-in-hole test using the Virtual Directional Pad solution. Similar to the previous test, the robot moves the end-effector to the pickup area where the user has to use gesture to guide the robot into an appropriate pickup location above the cylindrical component. Next, the pickup routine can be actuated by closing the right palm and the robot brings the component to near the target. In this test, the user has to position the object in line with the vertical hole using gesture and then drop the object into the hole by releasing the right palm (figure 4-4). The fitting of the assembly has a tolerance of approximately 1mm. This peg-in-hole task has been performed five times by the researcher where four out of five consecutive attempts were successful. It was assessed the one failure was the result of the limitation in viewing angle and the lack of practice of the participant, which shows the importance of informative visual feedback during teleoperation.

Figure 4-4 - Peg-In-Hole test using Virtual Directional Pad

Although the tests performed have been mostly successful, it was concluded that this method of robot control has a number of drawbacks. Firstly, the potential to expand the functionalities of this particular system is difficult. For example, it is unintuitive to extend the 2D control to 3D control in Cartesian space. Secondly, the positioning of the robot gripper was difficult to achieve and time consuming due to the limitation in visual perspective and the skill required in accomplishing such tasks. Furthermore, this method can require significant physical workload over a prolong period of use.

4.3.4 Static pose gestures in industry

Subsequent to the Virtual Directional Pad development the research proceeded to seek a more sophisticated solution. A number of researches have investigated the feasibility of gesture recognition of common sign languages with different origins (Verma et al, 2013). However, these sign languages can require significant effort to learn. It was identified that existing industrial hand gestures are currently being used by building workers for crane operation in building sites. These gestures are standardised as described in BS ISO 16715. These gestures enable ground workers to direct the crane operator who sits in an operating room situated as high as 100m above the ground (Chow and Pickles, 2015). The gestures are designed to use both arms which provide signals that are clear to observe from a distance. The standard describes 26 gestures with a combination of directional gestures and operation commands. Some of the gestures require small movement such as rotation of the hand which can be difficult to observe. Ten of these gestures were selected based on their function which is suitable for the application of the developed system. Some gestures were simplified for more robust gesture recognition. The greatest challenge in developing a gesture control system is to design the system to be coherent for the user (Wigdor and Wixon, 2011). Using gesture designs based on standard ones can simplify the design process. These gestures can also be easily remembered, and therefore minimal training is required. From a human factors point of view, using simple gestures can minimise cognitive workload. The gesture set used in this system consists of ten gestures as illustrated in figure 4-5, six of them are directive gestures and three are command gestures. The directive gestures include left, right, raise, lower, forward and backward. These gestures can be used for selection or control a robot tool centre point to move in a direction in a predefined coordinate frame depending on the application. The command gestures include “Start”,” Stop”, and “Danger”. These gestures can be used to trigger or terminate a robot programme.

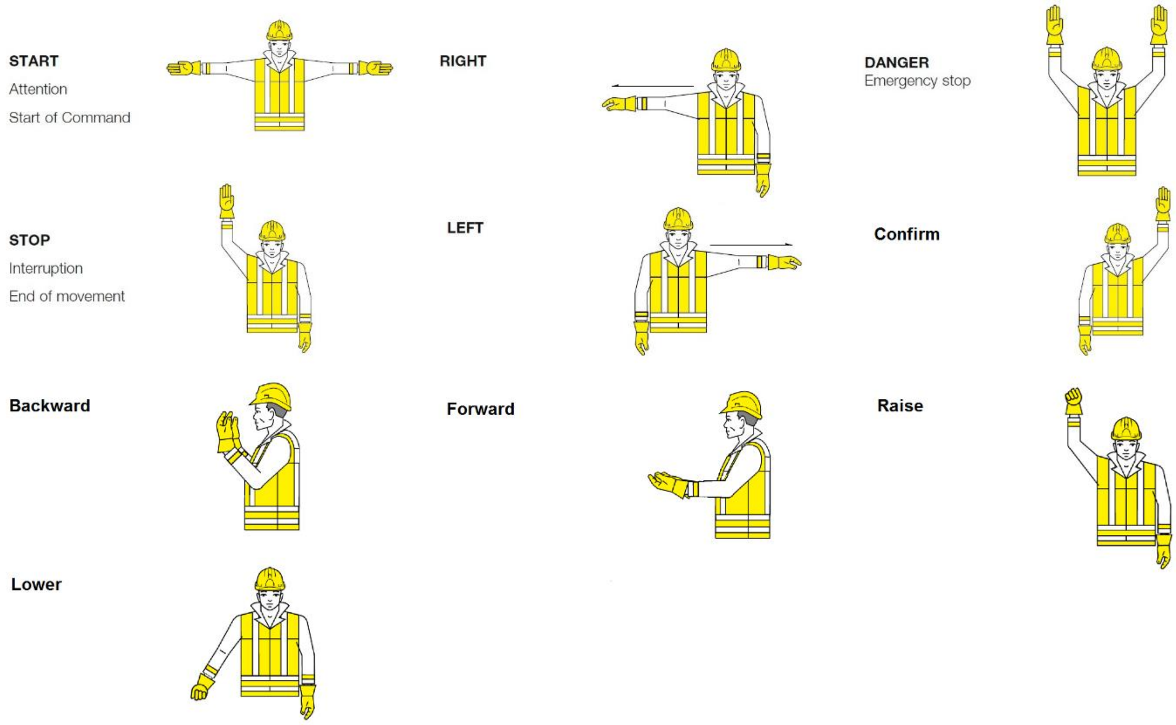


Figure 4-5 - gesture commands used in robot operation

The programme performs gesture recognition by analysing the user’s upper body 3D joints position at a rate of 30Hz. These include neck, right shoulder, right elbow, right wrist, left shoulder, left elbow, and left wrist. The body joints used in the recognition process are summarised in table 4-2 and illustrated in figure 4-6. The x (horizontal), y (vertical) and z (depth) values of each joint are constantly analysed by algorithms to seek for matching condition to any of the gestures, if all conditions are met then a gesture will be identified and a signal will be sent to the robot. For example, the “Danger” gesture requires the user to put both of their hands above their head as illustrated in figure 4-7. The system is designed for the robot to receive command from the user during operation in a workstation layout similar to the one illustrated in figure 3-2. To avoid false trigger, the system will only accept commands from the user when they are facing the robot, similar to human communication where people would look at each other during an interaction. In this case, the z values are used to monitor the level of attention of the operator towards the robot. This is explained in greater detail in chapter 4.3.5.

Table 4-2 - joints of interest and corresponding variables

Joint	Variables
Neck	(X_n, Y_n, Z_n)
Left shoulder	(X_{ls}, Y_{ls}, Z_{ls})
Left elbow	(X_{le}, Y_{le}, Z_{le})
Left wrist	(X_{lw}, Y_{lw}, Z_{lw})
Right should	(X_{rs}, Y_{rs}, Z_{rs})
Right elbow	(X_{re}, Y_{re}, Z_{re})
Right wrist	(X_{rw}, Y_{rw}, Z_{rw})

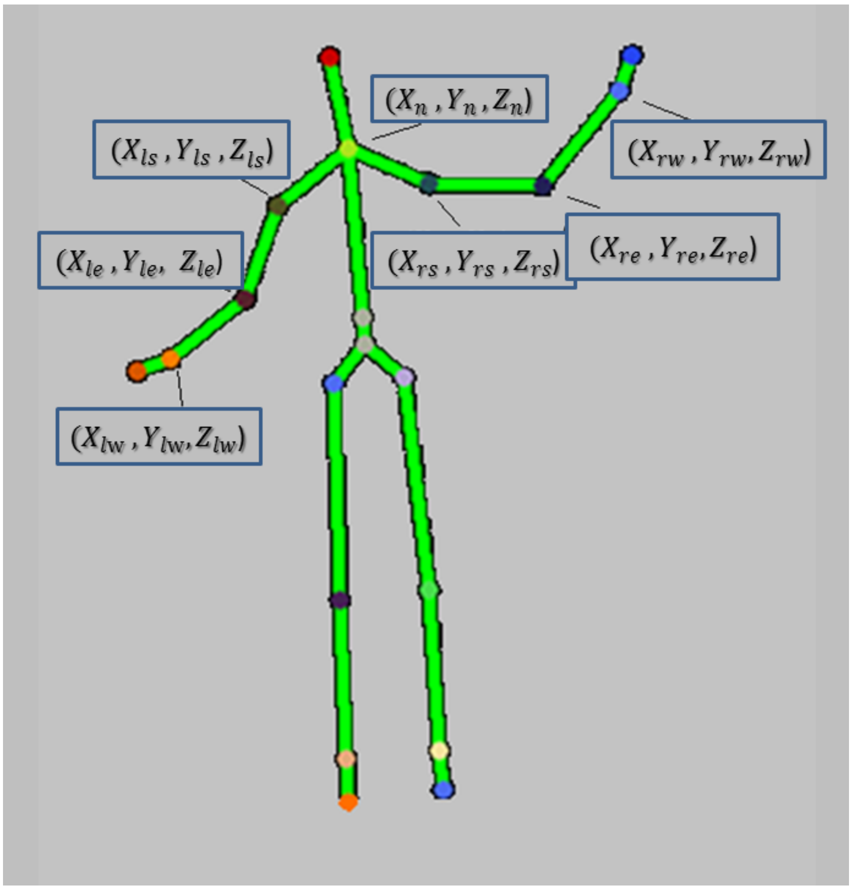


Figure 4-6 - Kinect skeleton with joint variables

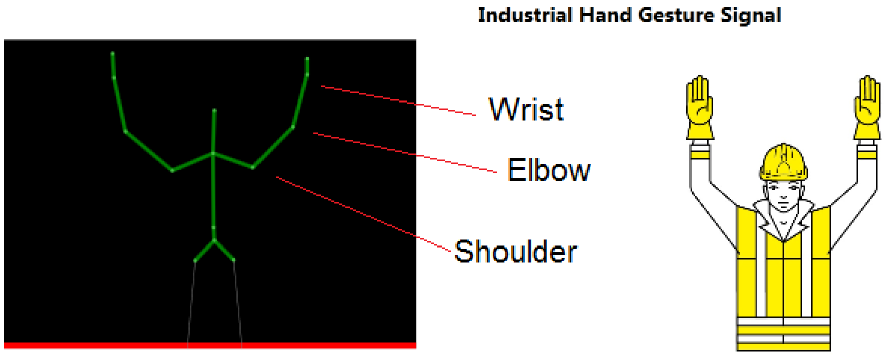


Figure 4-7 - gesture recognition software

4.3.5 Recognition algorithms

The Kinect API performs the human tracking and returns a number of joint coordinate values relative to the sensor position. These data are selected and used for classification of gesture. The gesture recognition algorithms recognise a gesture by matching conditions based on measurements of Euclidean distance between joint and joint angles. The adopted gesture set consists of gestures characterised by different variations of hand and arm positions. Thus, the user inputs have to fulfil several conditions in order to find a matching gesture. These conditions are segregated by the positions of left and right arm. Each gesture is defined by three conditions of the left arm α_l, β_l and γ_l, and three conditions of the right arm α_r, β_l and γ_r. The α condition must be met before the β and γ condition is being assessed which can be described in (1).

$$\alpha \rightarrow \beta \rightarrow \gamma \qquad \textbf{(1)}$$

This check is carried out simultaneously for both arms which can be described by (2).

$$|\alpha_l \rightarrow \beta_l \rightarrow \gamma_l| \,.\, |\alpha_r \rightarrow \beta_r \rightarrow \gamma_r| \tag{2}$$

The α and β are characterised by coordinate positions of the hand which vary between each gesture. The γ is defined by the angle θab which is the specific angle of the elbow required to be met by gesture. The angle of elbow is obtained using formula (3).

$$\theta ab = \cos^{-1}\left(\frac{Va.x * Vb.x + Va.y * Vb.y + Va.z * Vb.z}{\sqrt{Va.x^2 + Va.y^2 + Va.z^2} * \sqrt{Vb.x^2 + Vb.y^2 + Vb.z^2}}\right) * \frac{180}{\pi} \tag{3}$$

The inner elbow angle θab between wrist and shoulder on both arms must reach a calibrated threshold $\theta\mathrm{t}$ for the condition to take effect. The angle calculation between the lower arm vector Va and upper arm vector Vb is defined in (8). Note that both Va and Vb have three dimensions x, y and z where $Va.x * Vb.x + Va.y * Vb.y + Va.z * Vb.z$ is the dot product of Va and Vb.

To further enhance the robustness of the interface, the level of attention of the operator is monitored by the conditionOA. The condition OA ensures that the operator is standing straight and facing the robot while making the command. By comparing the depth value of the right and left shoulders and the neck, the condition OA can be checked. The condition can be met if the calculated value is within the upper and lower threshold τu and τl.This can be expressed as (4):

$$OA = \tau l < (Z_{ls} \cdot Z_n) - (Z_{rs} \cdot Z_n) < \tau u \tag{4}$$

The characteristics of each gesture and their conditions are described as follows.

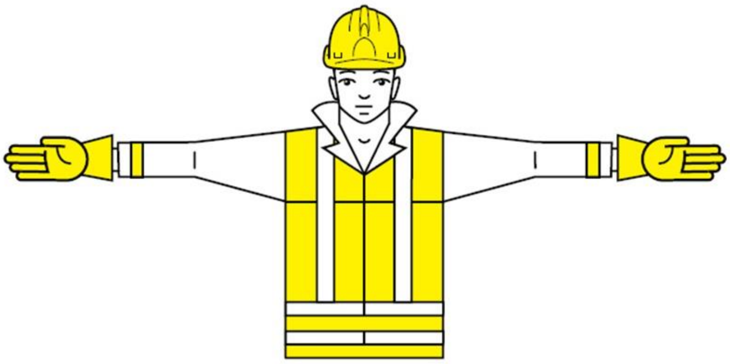


Figure 4-8- “start” gesture

The “start” gesture (figure 32) is used to begin an operation or a particular robot programme. This gesture requires the user to lift both of their arms to form a horizontal line, and both hands should be pointing away from the body. In algorithmic terms, both wrists should be on a similar horizontal level as the elbow and the shoulder as illustrated in (5-9).

$$\alpha_l = |x_n > x_{ls} > x_{le} > x_{lw}| \tag{5}$$

The wrist joint and the shoulder joint should be aligned at a similar horizontal level as show in (5). The constant e is applied to provide a tolerance.

$$\beta_l = |y_{lw} - y_{ls} < e| \tag{6}$$

A similar formula applies to the right arm as illustrated in (6) and (7).

$$\alpha_r = |x_{rw} > x_{re} > x_{rs} > x_n | \tag{7}$$

$$\beta_r = |y_{rw} - y_{rs} < e| \quad \textbf{(8)}$$

The γ condition of both arms require the elbow joints to be near 180degree, θe is the tolerance constant which can be adjusted to change the sensitivity as show in (8). A higher sensitivity may reduce the robustness of the system due to false trigger, but a tolerance must exist to accommodate the physical different between users. Some users may struggle to achieve a pose with completely straight arm.

$$\gamma = \theta ab \pm \theta e \quad \textbf{(9)}$$

Figure 4-9 - "stop" gesture

The “stop” gesture (figure 4-9) is used to stop an operation or confirm the end of a task. The operator should lift their right arm until their hand is above the top of their head and pointing towards the sky with an open palm. The rule of this gesture is to have the right hand positioned over the horizontal level of the head as illustrated in (10) and (11) while the other hand in natural position, and the elbow joint should be approximately 130degree.

$$\alpha_r = \begin{cases} |x_{rw} > \ x_{re} > \ x_{rs} > \ x_n \,| \,. \\ \ |y_{rw} > \ y_{re} > \ y_{rs} > \ y_n| \end{cases} \tag{10}$$

$$\beta_r = \ |x_w - \ x_e < e| \tag{11}$$

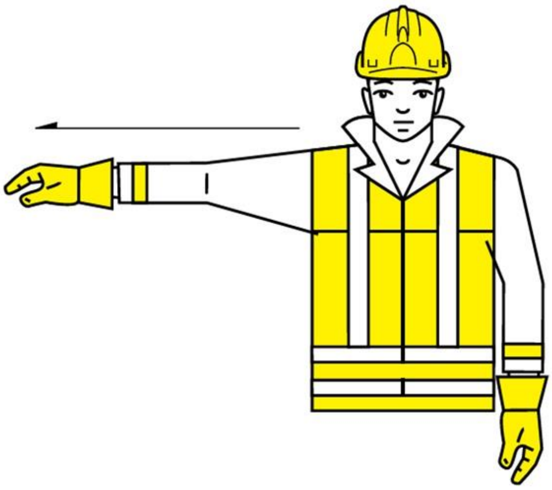


Figure 4-10 - "right" gesture

The “right” gesture (figure 4-10) in this case is used for selection purposes such as for choosing component to use or routine to start. The operator should hold the right arm at a horizontal level with the hand pointing away from the body. In this case, the right wrist is on the same horizontal level as the right elbow and shoulder as described in (12) and (13) while the left arm is at a neutral position pointing downwards.

$$\alpha_r = |x_{rw} > x_{re} > x_{rs} > x_n| \tag{12}$$

$$\beta_r = |y_{rw} - y_{rs} < e| \tag{13}$$

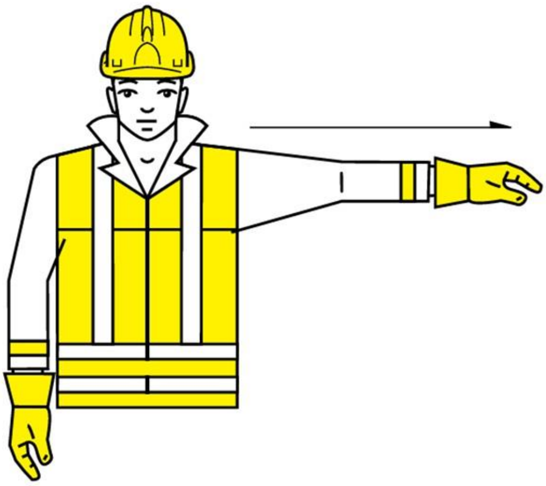


Figure 4-11 - "left" gesture

Similarly, the “left” gesture (figure 4-11) is also for selection purposes. The operator should hold their left arm at a horizontal level with the left hand pointing away from the body. The left wrist is on the same horizontal level as the shoulder as illustrated in (14) and (15) while the right arm is at a neutral position pointing downwards.

$$\alpha_l = |x_n > x_{ls} > x_{le} > x_{lw}| \tag{14}$$

$$\beta_l = |y_{lw} - y_{ls} < e| \tag{15}$$

Figure 4-12 - "confirm" gesture

The “confirm” gesture (figure 4-12) can be used to confirm a decision or selection. The pose is the opposite of the “stop” gesture where the operator should lift their left arm until their hand is above the top of their head and pointing upwards, the conditions for left hand is described in (16) and (17). The elbow joint should be approximately 130degree.

$$\alpha_l = \begin{cases} |x_n > x_{ls} > x_{le} > x_{lw}| \cdot \\ |y_{lw} > y_{le} > y_{ls} > y_n| \end{cases} \tag{16}$$

$$\beta_l = |x_{lw} - x_{le} < e| \tag{17}$$

Figure 4-13 - "danger" gesture

The danger gesture (figure 4-13) should only be used when an operator senses a hazard. However, the robot system should be designed in way that no hazardous incident would occur and safe for operator to work with under any circumstances. To trigger the emergency function, the operator has to lift both of their arms until both hands are above the head level. In algorithm terms, this gesture is to have the both wrists positioned over the horizontal level of the head (18-21), and both elbow inner joint angles should be approximately 130degree which is processed using (8).

$$\alpha_l = \begin{cases} |x_n > x_{ls} > x_{le} > x_{lw}| \cdot \\ |y_{lw} > y_{le} > y_{ls} > y_n| \end{cases} \tag{18}$$

$$\beta_l = |x_{lw} - x_{le} < e| \tag{19}$$

A similar formula applies to the right arm.

$$\alpha_r = \begin{cases} |x_{rw} > x_{re} > x_{rs} > x_n| . \\ |y_{rw} > y_{re} > y_{rs} > y_n| \end{cases} \tag{20}$$

$$\beta_r = |x_w - x_e < e| \tag{21}$$

Figure 4-14 - "raises" gesture

The “raise” gesture (figure 4-14) is somewhat similar to the “stop” gesture, the only difference is the closed palm. It is used for directional control purpose. The operator should lift their right arm until their hand is above the top of their head with their palm closed. The rule of this gesture is to have the right hand positioned over the horizontal level of the head with palm closed as illustrated in (22) and (23) while the other hand in natural position, and the elbow joint should be approximately 130degree.

$$\alpha_r = \begin{cases} |x_{rw} > x_{re} > x_{rs} > x_n| \, . \\ |y_{rw} > y_{re} > y_{rs} > y_n| \end{cases} \tag{22}$$

$$\beta_r = |x_w - x_e < e| \tag{23}$$

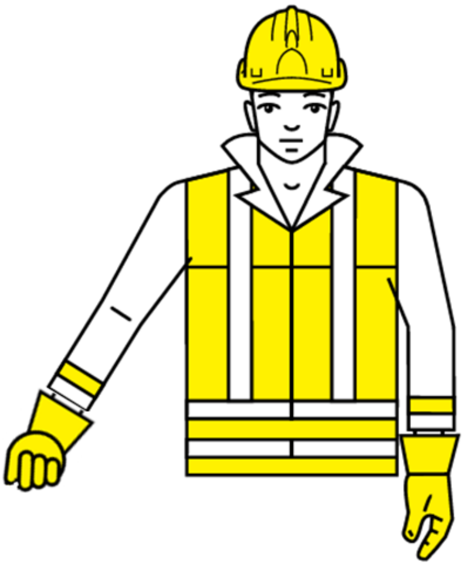


Figure 4-15 - "lower" gesture

The “lower” gesture (figure 4-15) does the opposite to the “raise” gesture which is used for lower direction control. The operator should point their right arm downward slightly away from their body with their palm closed. The rule of this gesture is to have the right hand positioned below the horizontal level of the elbow and shoulder. The wrist should be pointing away from the torso centre line as illustrated in (24) and (25) while the other hand in natural position, and the elbow joint should be approximately 130degree.

$$\alpha_r = \begin{cases} |x_{rw} > x_{re} > x_{rs} > x_n| \, . \\ |y_{rw} < y_{re} < y_{rs}| \end{cases} \tag{24}$$

$$\beta_r = |x_w - x_e < e| \tag{25}$$

Figure 4-16 - "backward" gesture

The “backward” gesture is used for directional control which indicates movement towards the operator. The operator should raise both of their hands to the front of their chest around the horizontal level of their neck. The rule for this gesture is to have both wrists positioned in front of the elbows and the neck, at a horizontal level similar to the neck. The algorithms for both arms are illustrated in (26) and (27).

$$\alpha = \{|Z_w < Z_e < Z_s < Z_n | \tag{26}$$

$$\beta = |Y_w - Y_n < e| \tag{27}$$

Figure 4-17 - "forward" gesture

The “Forward” gesture is used for directional control which indicates movement away from the operator. The operator should hold both of their forearms horizontally in front of them with curled elbows as illustrated in figure 4-17. The rule for this gesture is to have both wrists positioned in front of the elbows and the neck, at a horizontal level similar to the elbows. The algorithms for both arms are illustrated in (28) and (29).

$$\alpha = \{|Z_w < Z_e < Z_s < Z_n | \tag{28}$$

$$\beta = |Y_w - Y_e < e| \tag{29}$$

For most gestures, there is a short initiate delay and this is to minimise recognition error caused by unintended movements which can be similar to a certain gesture. An exception has been made for the “Danger” gesture, because it is an emergency function to be used when a hazard occurs. The recognition program for this particular gesture is run simultaneously to the other gesture recognition program, and it can be activated even by unregistered users within the sensor's range with immediate effect. However, this is only to cover hazardous situation where the robot may collide with another component. The robot shall be setup in a way that should never cause any harm to people according to ISO 10218:2011.

4.3.6 Evaluation

Initial testing have revealed that some of the gestures suffer from ambiguity with normal activity or other gestures. These gestures include forward, backward, lower and raise. For example, the forward and backward gestures can appear similar to natural postures during a manual task, especially when both hands are positioned in front of the person's body. The lower gesture could be triggered accidentally in a natural pose while the raise gesture could be confused with the stop gesture with the only difference being opened and closed palm. For these reasons, these four gestures are impractical to use in this system. However, the remaining six gestures continue to be valuable to use as command gestures and they were evaluated using a number of participants.

The SPR programme was tested in a laboratory environment. Each of the six gestures were given a gesture ID (table 4-3) and grouped in a number of randomised sets to minimise the order effect (table 4-4). Each gesture set is consisted of the six gestures in different sequence and this is to allow detection of false triggers cause by transition from one gesture to another. Six staffs of Cranfield University (4 male and 2 female, height: M=175.67cm, SD=7.42cm) took part in the test and each of them was given five sets of gestures to perform. Participants had to hold each pose for approximately 3 seconds, the accuracy of gesture recognition is measured based on the ability of the system to recognise the gesture within the given 3 seconds. The Kinect was setup at a height of 138cm and the participant were standing approximately 200cm from the sensor. Prior to the test, the participants were briefed about the experiment and instructed to perform the gestures in a specific order. An A3 printout of the list of gestures in Figure 4-5 was positioned in front of the participants throughout the test.

Table 4-3 - gesture and gesture ID

Gesture	ID
start	1
stop	2
left	3
right	4
danger	5
confirm	6

Table 4-4 - Static Pose Recognition test sequence

Test sequence						
Set	Gesture ID					
1	1	2	3	4	5	6
2	1	3	4	5	6	2
3	1	4	5	6	2	3
4	1	5	6	2	3	4
5	1	6	2	3	4	5
6	2	3	4	5	6	1
7	2	4	5	6	1	3
8	2	5	6	1	3	4
9	2	6	1	3	4	5
10	2	1	3	4	5	6
11	3	4	5	6	1	2
12	3	5	6	1	2	4
13	3	6	1	2	4	5

14	3	1	2	4	5	6
15	3	6	1	2	4	5
16	4	5	6	1	2	3
17	4	6	1	2	3	5
18	4	1	2	3	5	6
19	4	2	3	5	6	1
20	4	3	5	6	1	2
21	5	6	1	2	3	4
22	5	1	2	3	4	6
23	5	2	3	4	6	1
24	5	3	4	6	1	2
25	5	4	6	1	2	3
26	6	1	2	3	4	5
27	6	2	3	4	5	1
28	6	3	4	5	1	2
29	6	4	5	1	2	3
30	6	5	1	2	3	4

4.3.7 Results

The experiment results from the Static Pose Recognition programme test is shown in Figure 4-18. It shows that the “start” and “right” gestures were recognised with 100% accuracy. The “left” gesture has 96.7% accuracy and “stop”, “danger” and “confirm have 93.3% accuracy. The accuracy is measured based on the recognition of the first attempt of the participant performing the pose. All the poses that were not initially recognised have been recognised after slight adjustment of the arm position. Gestures that involve positioning one or both hands above the head receive the lowest accuracy, and most of these errors happened with two participants who did not position their hands high enough so improved training may increase the accuracy in the future. This problem can also be solved by increasing the value of the threshold. As mentioned previously, the robot setup should be carried out compliant to ISO 10218:2011 to ensure all the safety aspects are well thought-out, and under no circumstances should the malfunction of the gesture control poses safety threat to the user. Furthermore, the practicality of these static pose commands can be enhanced by combination with dynamic hand tracking motion control which enable user to make commands to the robot as well as controlling its motion in 3D. This integration is discussed in chapter 4.5.

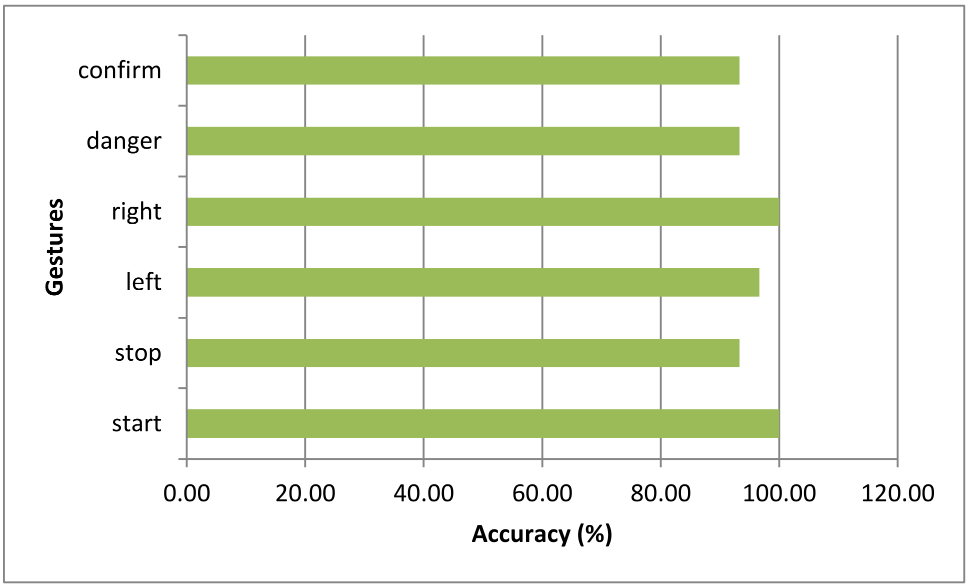


Figure 4-18 - Accuracy of Static Pose Recognition programme (%)

4.4 Dynamic Hand Motion Tracking (DHMT) control

4.4.1 Introduction

In addition to the SPR, the DHMT control mechanism enables the user to control the robot’s movements by moving one of their hands. As mentioned previously, there are a number of researches conducted on developing this type of gesture control system for robots. However, in a practical situation industrial robots are often installed in a restricted space with obstacles such as walls within the robot’s working envelope. Furthermore, the majority of industrial robots have no safe force torque limit unlike the one used in this system, and therefore a human operator should be separated from the robot by a safety distance which is calculated by the safety distance formula described in EN ISO 13855:2010 (British Standards Institution, 2010). The safety distance formula takes a number of factors into account which include the robot speed, if the robot is programmed to match a human’s hand speed which can be over 2m/s (Elgendi et al, 2012) then human integration will be prohibited, because the human operator will be separated by a safety distance of over 2m, also Arai et al (2010) have found that a robot moving at speed greater than 1m/s in a collaboration can causes fear and surprise to human operator . Thus, full control with this technique is not feasible. Nevertheless, this type of control method is valuable for applications where guidance of robot through a specific path is required. Although safety distance is not an issue with the robot used in this research, the gesture control is still designed as a subsystem with appropriate restrictions, and these restriction parameters will allow the system to be adapted for use with other robots in the future.

4.4.2 System architecture

The system architecture of the DHMT system is illustrated in figure 4-19. Similar to the SPR, the raw sensor data are processed by the sensor API which recognises and tracks the user. The tracking data are processed by the DHMT algorithm and relevant outputs are encoded and then sent to robot system. The robot programme decodes the incoming data and the robot moves according to the user input.

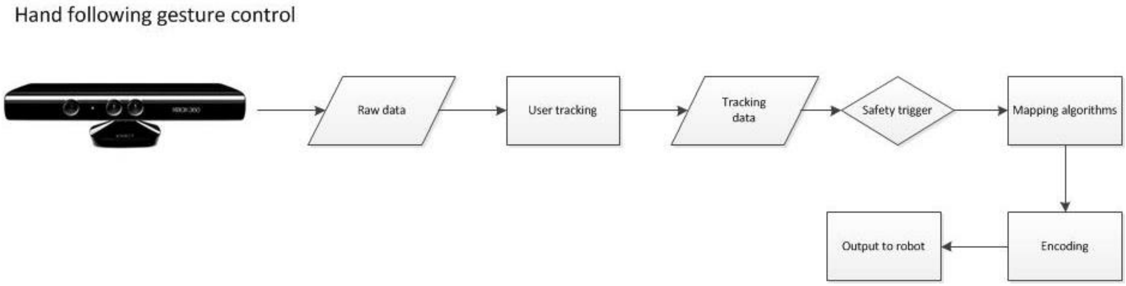


Figure 4-19 - system architecture of DHMT

4.4.3 Hand calibration and mapping

For DHMT control the system constantly tracks the position of the user's right hand while monitoring the state of the left fist for activation and deactivation as illustrated in figure 4-20. During every activation the current hand position $C(c_x,c_y,c_z)$ is saved in temporary memory for calibration. The tracked hand position data $H(h_x,h_y,h_z)$ are calibrated using recorded hand origin $C(c_x,c_y,c_z)$ which gives $UH(uh_x,uh_y,uh_z)$ as presented in (22). The operator's right hand movement range is defined by $\left(H_{x,y,z}^{max} - H_{x,y,z}^{min}\right)$ while $(W_{x,y,z}^{max} - W_{x,y,z}^{min})$ gives the range of the robot's work space. The hand position data are scaled based on $\left(H_{x,y,z}^{max} - H_{x,y,z}^{min}\right)$ and $(W_{x,y,z}^{max} - W_{x,y,z}^{min})$ using the algorithm presented in (23) which gives $R(r_x,r_y,r_z)$.

$$UH = H - C \tag{22}$$

$$\begin{cases} R_x = \dfrac{\left(UH_x - H_x^{min}\right) * (W_x^{max} - W_x^{min})}{(H_x^{max} - H_x^{min})} + W_x^{min} \\ R_y = \dfrac{\left(UH_y - H_y^{min}\right) * (W_y^{max} - W_y^{min})}{(H_y^{max} - H_y^{min})} + W_y^{min} \\ R_z = \dfrac{\left(UH_z - H_z^{min}\right) * (W_z^{max} - W_z^{min})}{(H_z^{max} - H_z^{min})} + W_z^{min} \end{cases} \tag{23}$$

$$Rw = CP + R \tag{24}$$

The robot movement point $\mathrm{Rw}(\mathrm{rw}_x,\mathrm{rw}_y,\mathrm{rw}_z)$ is result of the robot current tool centre point (TCP) $\mathrm{CP}(\mathrm{cp}_x,\mathrm{cp}_y,\mathrm{cp}_z)$ added with the dynamic hand tracking output $\mathrm{R}(\mathrm{r}_x,\mathrm{r}_y,\mathrm{r}_z)$ as illustrated in figure 4-20.

The virtual work plane is predefined in the robot controller using three or more points, a number of work planes can be created within the robot controller to support different applications, and this can be carried out with most robot controllers, thus enabling the system to be applicable on other industrial robots in a different scale. Each plane has its own coordinate system Rf and the robot movement bounding box will be defined based on these work planes.

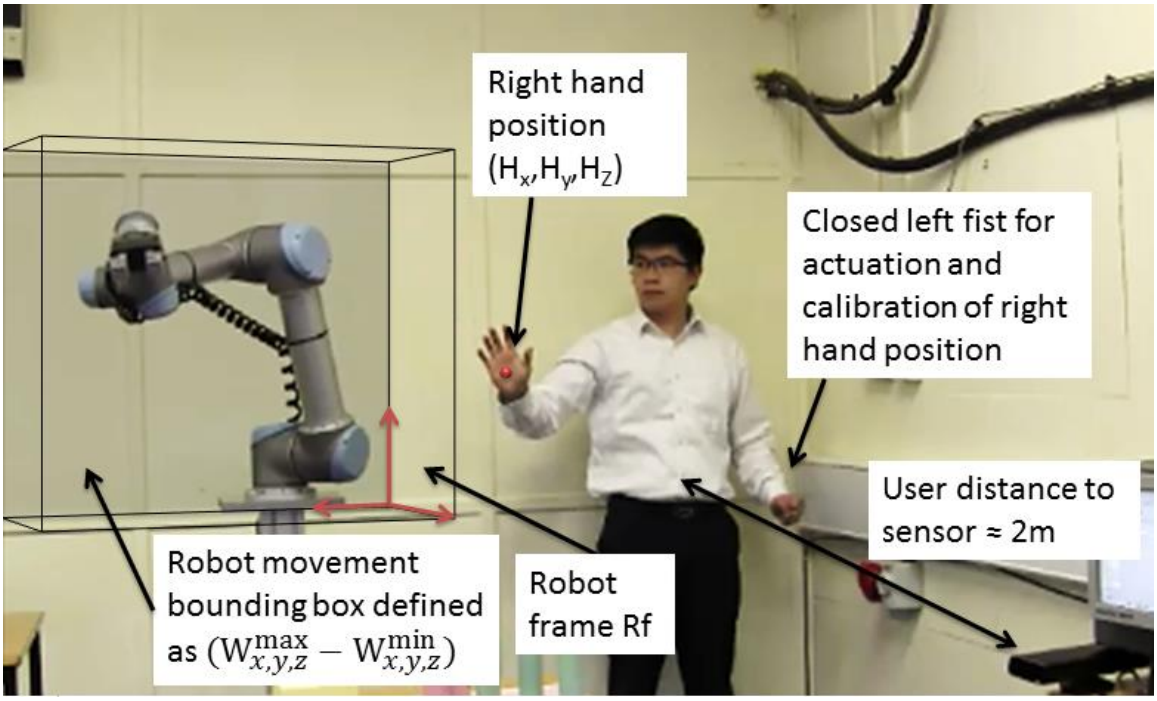


Figure 4-20 - gesture control with right hand controlling movement and left hand for actuation, picture on the right showing robot's working area

The functionality can provide the user with the ability to control the robot's movement in real-time to carry out tasks. This is particularly useful for manufacturing applications with high variation and required delicate movement control of the end-effect, for example polishing.

4.4.4 Methods

The hand tracking capability of the Kinect is critical for the DHMT system, thus it was tested with a calibrated laser tracker to make comparisons of hand movement paths. The Kinect was positioned 60cm from the laser tracker at a lower level and both devices were approximately 1.8m from the participant standing point. The chosen distance between the participant and the sensors enables the Kinect to capture all the possible movements of the participant as well as to simulate human-robot interaction as described in chapter 3.3 (assuming the sensor is mounted at the robot base). The effect of the separation distance between human and the Kinect on the tracking accuracy is discussed in chapter 3.6.1. The purpose of this setup was to make direct comparisons between the two devices, and therefore initially the participant was to hold a laser tracker reflector ball in the right hand to perform the movement allowing both devices to record identical hand movement paths. However, it was found that the Kinect struggled to track the participant's hand on many occasions while holding the reflector ball, and hence an alternative method was used. Instead a rectangular frame was built to enable hand movements to be performed repeatability with similar paths. The frame was constructed using aluminium tube with 4cm x 4cm cross-section and the rectangle measured 45cm x 42cm, additional guiding sticks were placed at the 4 corners of the rectangle so that operator's hand could move in front of the frame to avoid obstruction of the Kinect's view. The Kinect data used in this test are extracted from the right hand joint of Kinect SDK skeleton tracking. More tests were carried out after this with the Kinect Interaction hand tracking feature, which was the selected tracking method for this system.

4.4.5 Evaluation

To test the hand tracking accuracy, a number of measurements were taken using the laser tracker and Kinect separately and comparisons were then made. Figure 4-21 shows a scatter plot of laser tracker data and Kinect skeleton data. The Kinect skeletal data has been converted to a real-world coordinate system to match the laser tracker results. The results show data for hand movements around the rectangular frame 4 times. The purpose of this test was to show graphical correlations between the two sets of data in terms of coordinates, position and rectangle size.

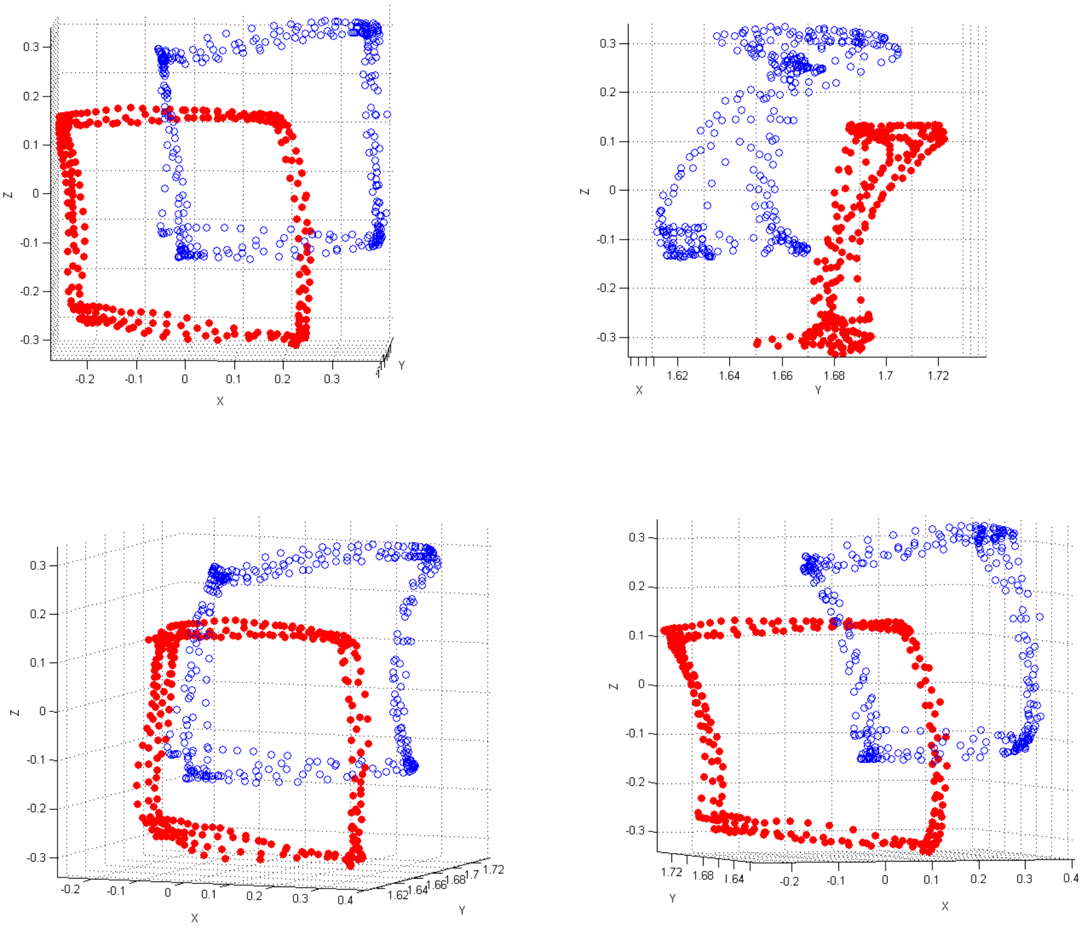


Figure 4-21 - comparison of laser tracker (red) and Kinect skeleton raw results (blue), which illustrate similarity in shape and size of rectangular measurement

The results showed that the rectangle measured with the Kinect is comparable in size with those measured with a laser tracker. The Kinect data points overlap the laser tracker data in the X-Z axes after conversion to the real-world coordinate system. More tests have been carried out using these devices. Each device was used to take 5 sets of single loop measurement to make comparison on the length of both sides of the rectangle. The maximum differences in the spread of lengths among 5 sets of data were 6.3mm, 9.7mm and 0.7mm (to 1 decimal place) in x, y and z respectively. The spread of axis length measurements from 5 sets of coordinate data were plotted for both devices to make comparisons as illustrated in figure 4-22. The rest of the results are summarised in table 4-5. Although the differences were consistent for all of the data sets, the Kinect skeletal tracking hand data contained noise, which can be caused by occlusion from the aluminium structure for hand guidance.

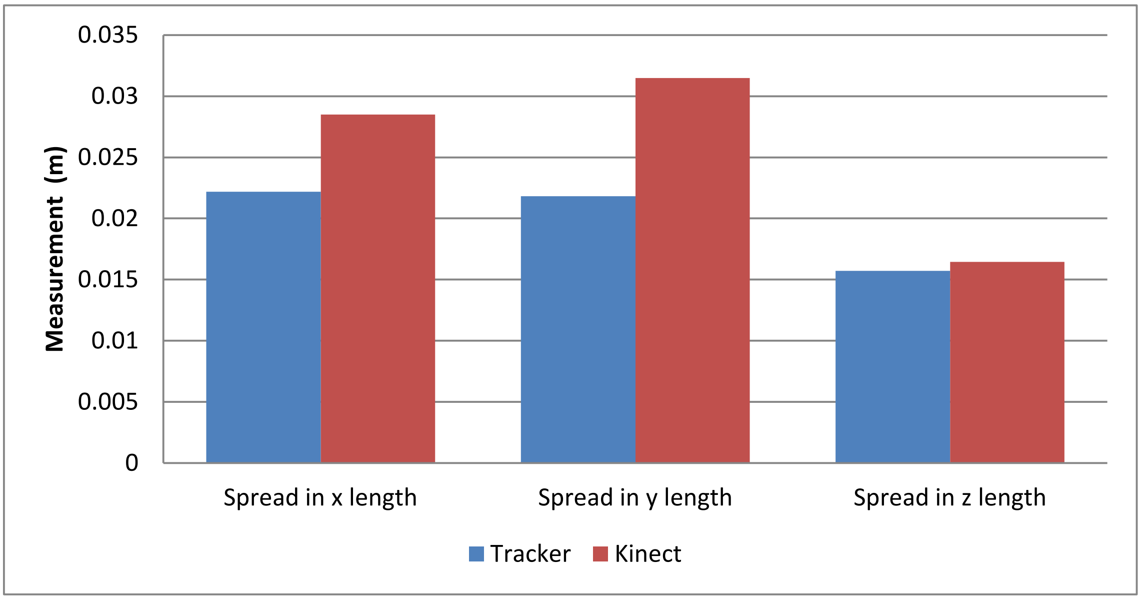


Figure 4-22 - the graph is showing the means of 3D coordinate ranges measured by the two devices

Table 4-5 - Kinect vs Tracker results

Length measurement	Kinect (mm)	Tracker (mm)	Difference (mm)
Mean x	488.47	526.19	-37.72
Mean y	460.48	476.68	-16.2
Mean z	82.58	50.25	32.33
Median x	483.5	522.7	-39.2
Median y	459.69	476.43	-16.74
Median z	83.81	51.16	32.65
Standard deviation x	11.68	8.99	2.69

Standard deviation y	6.05	9.04	-2.99
Standard deviation z	11.35	7.56	3.79

An alternative method of tracking hands with the Kinect SDK is Kinect Interaction hand tracking. The feature was introduced to be compatible with Kinect-enabled PC applications. The feature uses depth information and skeleton tracking information to track a user’s hands. This feature was selected to support the gesture control system due to its capability to detect the hands’ state such as grip and release. In this test, the Interaction hand pointer’s coordinates were compared against skeleton tracking’s right hand joint data for identical hand movements.

The Kinect Interaction hand pointer has a different coordinate system compared to the skeleton tracking as well as scale, the interaction hand pointer is also more sensitive in the z direction to measure how much a pressing movement is being performed by hand. The plots in figure 4-23 show that the interaction hand pointer data has a similar shape as the skeletal tracking data. It is also noticed that the interaction hand pointer data shows significantly less noise compared to the raw skeleton tracking data and resulted in a much smoother line plot as shown in figure 4-24, which indicates that built in filters are used in producing these outputs.

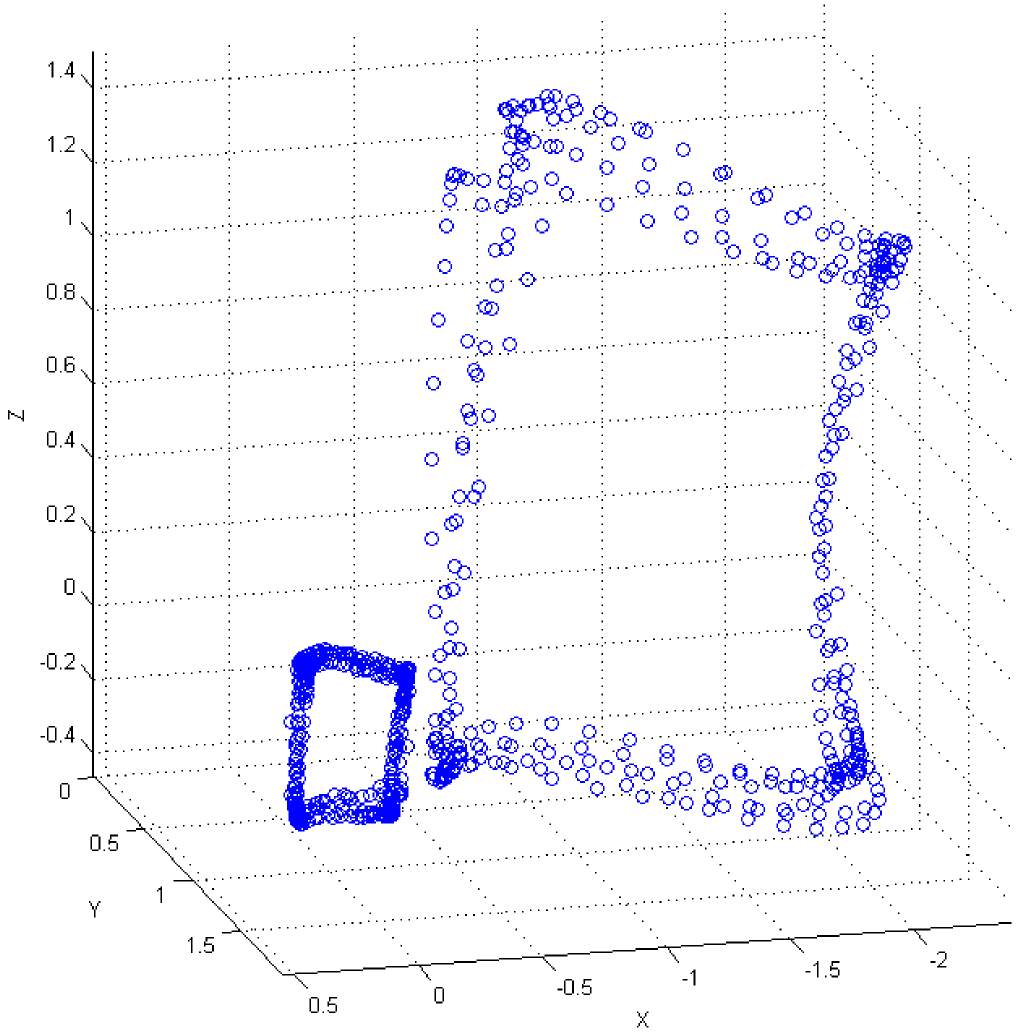
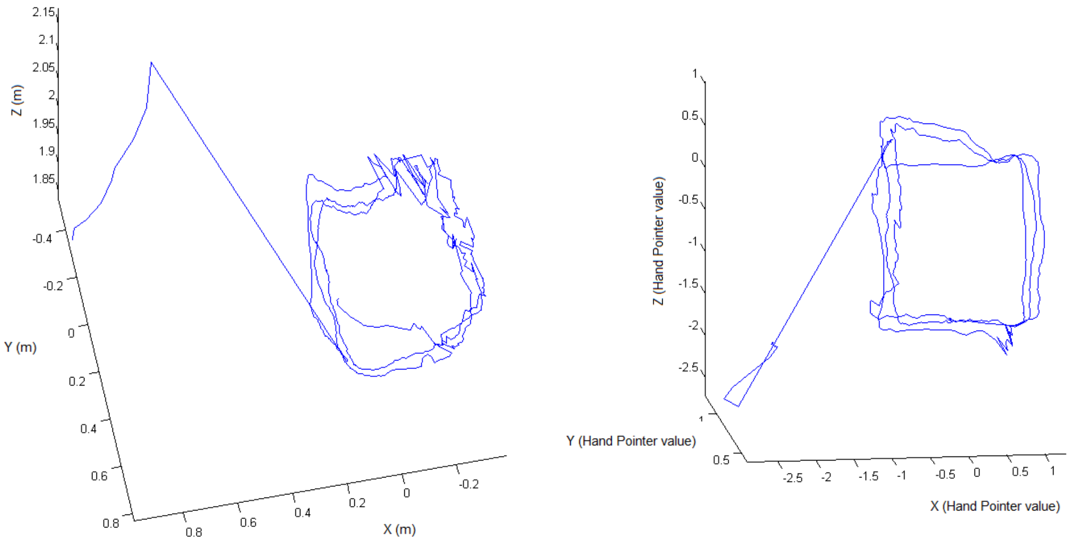


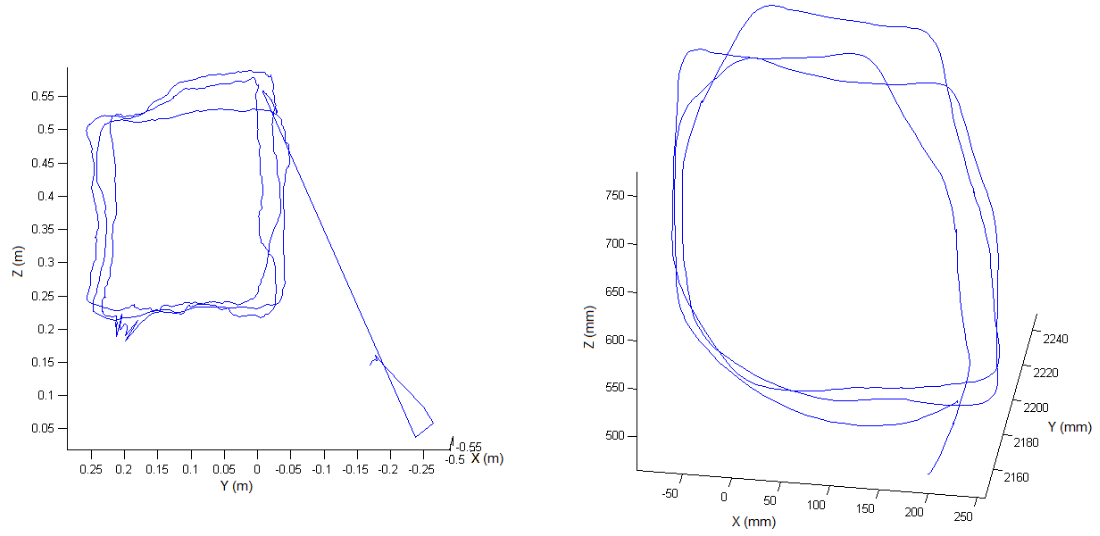
Figure 4-23 – Comparison of Kinect Skeleton (left) and Kinect Interaction hand pointer (right) results of hand movements in a rectangular shape path

Furthermore, the hand movement path following capability of the system was tested using a laser tacker and reflector on the robot end-effector sampling every 100ms. The hand movements tracked by the Kinect Skeleton, Interaction hand pointer, and output coordinates as well as robot movements are illustrated as line plot in figure 4-24. The results show that the robot movements resemble the same shapes as user input. The laser tracker measurement appears to be smoother than the Kinect measurements and one of the reasons is due to the difference in sampling frequency.



Kinect SDK Skeleton data

Kinect Interaction Hand Pointer data



Output data to robot

Laser tracker measurement of robot movement

Figure 4-24 - hand drawn shapes using Kinect to test usability to direct a path

For gesture motion control, the accuracy of the robot motion is wholly reliant on the hand coordinates input obtained using the Kinect which has been tested as described as well as the scale factor applied in the coordinates mapping. The accuracy of the robot movement following computer output has been tested by length comparison of movement lines with the robot working area restricted to a 540mm x 600mm x 230mm bounding box. Errors have been calculated based on 9 sets of computer output and tracker measurements. These results are summarised in table 4-6:

Table 4-6 - summary table of robot movement errors compare to control output

	Error	Percentage error
Mean	0.08mm	0.02%
Median	0.07mm	0.02%
Standard Deviation	1.44mm	0.36%

The errors of the Kinect hand tracking data can be reduced by the application of appropriate filters as demonstrated in a number of literatures. The errors in robot movement can be amplified or reduced depending on the ratio of hand motion range to size of robot working area. A larger robot working area will result in greater error relative to hand tracking data and the opposite with a smaller working area.

4.5 Integration of SPR and DHMT: a demonstration of application

This chapter describes the integration of two different types of gesture control systems for human-Robot collaboration. The purpose of this integration is to demonstrate the potential applications of gesture control in human-robot collaboration and the benefit and drawback of the methods. It is the final evaluation of the first iteration of the system development cycle. This work was carried out in collaboration with another researcher. The author of this thesis was responsible for leading the gesture control development and carrying out the main development where the other researcher has built the communication interface for distributed control of sub-systems.

The integrated system allows multiple operators to communicate commands and simultaneous motion tasks to an industrial robot using both hand gesture poses and hand-arm motion that would naturally be used to carry out tasks. The aim is to enable smooth transition between operating modes in collaboration which minimises downtime during human intervention in a robot task. The DHMT control can be carried out in 2D or in 3D depending on the requirements of the practical application. A set of gesture commands has been defined as described in chapter 4.3.4 since there is currently no standardised set of gestures for industrial collaborative robots. It has been taken into consideration that the developed system and gesture set will have wider applications in the future, and therefore it should be applicable onto industrial robots made by different manufacturers.

The novelty of the research presented in this chapter is the combination of standardised industrial gesture as well as dynamic hand tracking for input methods which provide an intuitive interface and allow for a direct control of robot motion. Furthermore, a facial recognition is embedded in the developed system as a management tool which to enable authorisation which is capable of determining level of authority and provides different type of control to specific user.

4.5.1 System Architecture

The system architecture consists of a number of subsystems at software level which are controlled by the control software (figure 4-25). Facial Recognition, Static Pose Recognition (SPR) and Dynamic Hand Motion Tracking (DHMT) are three sub-systems. Facial recognition is used to verify users who are authorised to use the system and recognise the user once they need to use the system. Registered users can be assigned with different levels of permission over the control of the system. For example, there can be two main roles in the system as follows:

1. Supervisor: A user who is authorised to use both the SPR and DHMT systems to start and stop the process, as well as the movement control of robot.
2. Technical worker: A user who is authorised to use only the DHMT system to control the movement of robot.

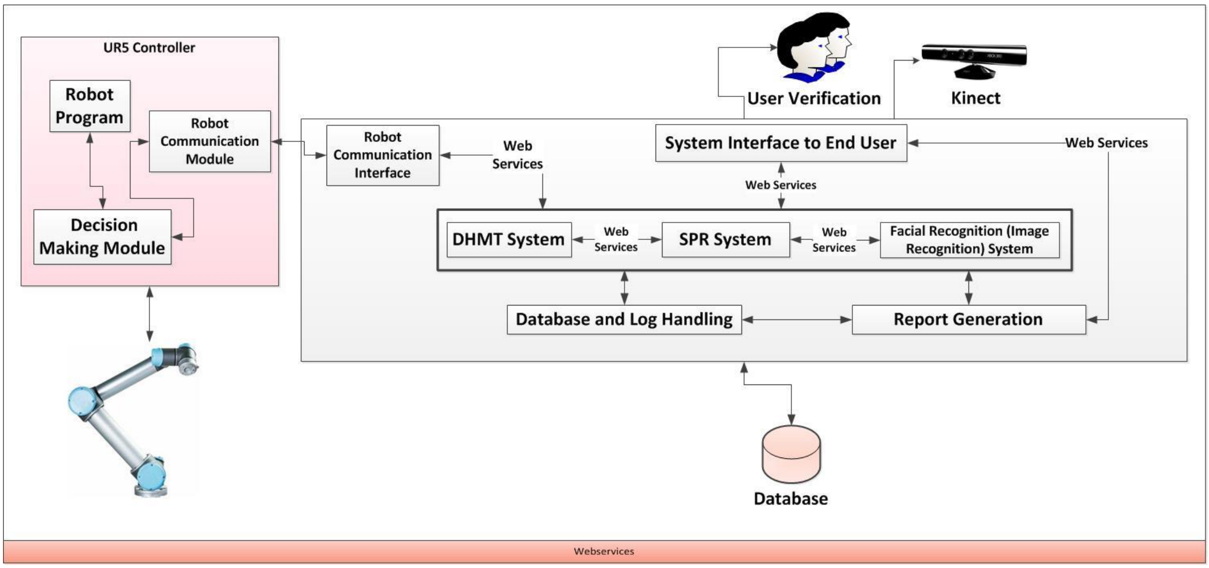


Figure 4-25 - System High Level Architecture

Figure 4-26 shows the flow of the information between the functions of system. Once the supervisor is recognised by the facial recognition system the control is passed to the SPR system where the supervisor can carry out selection, alignment, and start/stop the system. The system is capable of restart after an emergency stop without the need to reach the robot controller. Once the system is restarted, the supervisor (if required) can pass the control to a technical worker who can then control the movement of robot using DHMT and can complete the task. After finishing the task the control can be passed to supervisor who can stop the system. The emergency stop function can be used by anyone within the sensor's detection range using the "danger" pose to immediately stop the robot even if the system is in the DHMT control mode. The restart of the system can only be carried out using a hand signal by the supervisor who can then pass the control back to technical worker again.

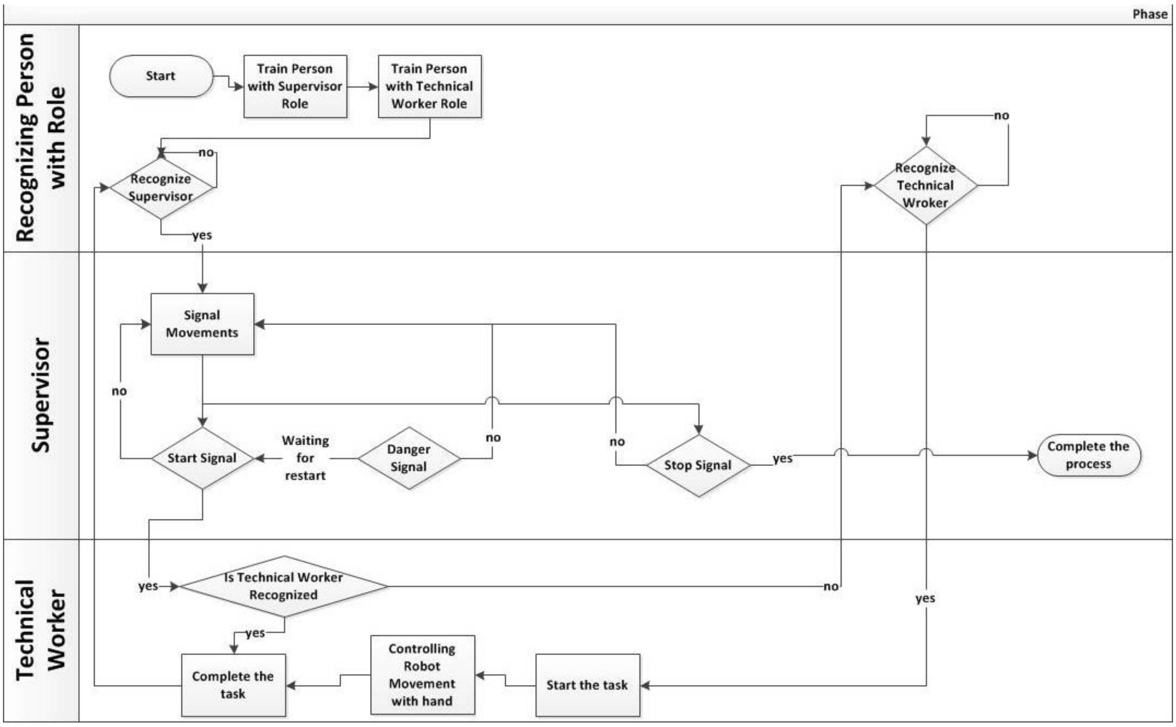


Figure 4-26 - Flowchart for Industrial Gesture Control System – a sample application

The system is modular and distributed in nature and can be installed on multiple computers connected through Ethernet or via an internet. For example, the supervisor can control the robot activation and de-activation from a remote location while operators perform robot motion control on the manufacturing line. A single sensor can be used as a shared resource in the system, but multiple sensors setup can also be adopted.

4.5.2 Facial recognition

The robustness and reliability of the gesture control system have been enhanced using facial recognition. As illustrated in figure 4-25 and figure 4-27, the system requests user verification at the beginning of the process, a user database consisting of facial data and level of authority is used for user identification. Once a user has been recognised, the system will assign the appropriate level of control and the user can carry out commands using gesture control.

The facial recognition engine is developed using the Eigenfaces approach for its simplicity and efficiency (Turk and Pentland, 1991). The system can track a person's head and recognise a person by performing Principal Component Analysis (PCA) comparing facial features to pre-recorded facial data in a database. The training data set is recorded using the Kinect under similar lighting condition as the actual operating environment to ensure the training data is of good quality for carrying out recognition. The training procedure is carried out for at least five times for each person at different angles to ensure the recognition to be reliable when the users turn or tilt their body away from the camera.

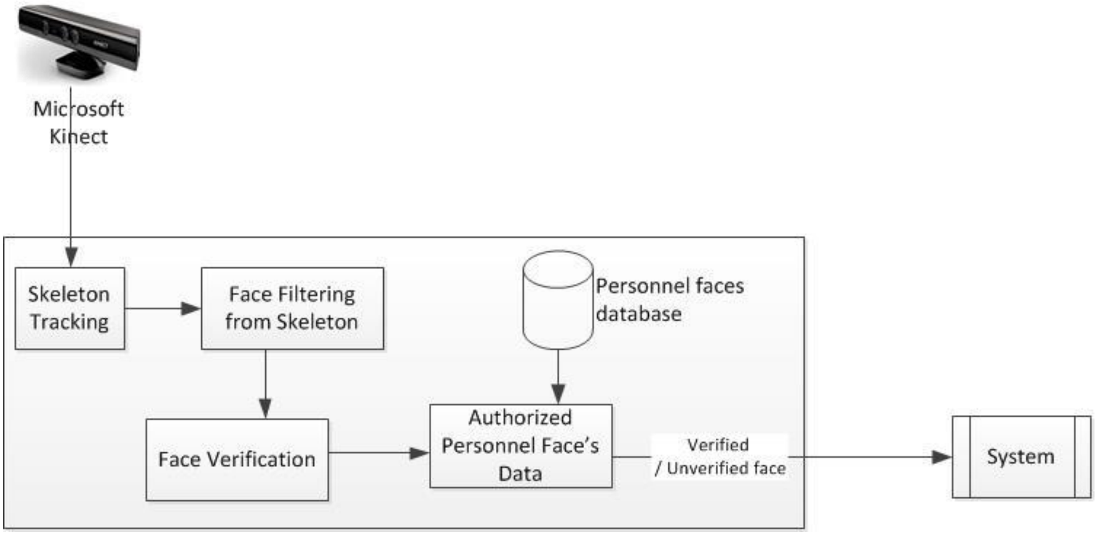


Figure 4-27 - Facial Recognition System

4.5.3 Evaluation

The three sub-systems were tested in isolation before the complete system was integrated, after the integration a sample task has been performed using the system to demonstrate the potential application of using a combination of different gesture control methods.

The face recognition system is not the focus of this development, but it has been tested for completeness. The program has been tested a number of times with 7 participants. The Eigenfaces method is a well-established method which is relatively simple to build and apply, and it is sufficiently reliable for a number of applications. However, it was found that the face recognition can be greatly affected by difference in lighting condition between image training and operation. The face recognition program has been reliable throughout the tests, but it is recommended to have at least five training images with different orientations of the face which include the front view for each person to achieve maximum reliability.

The effectiveness of the integrated gesture control system was tested using a pick and polish task with multiple operators. A test bench was positioned within the robot's working envelope consisting of a storage area and polishing area as illustrated in figure 4-28. The storage area had three cylindrical components located in a part holder, and the polishing area was fitted with a rotational polishing device. Each test involved two participants, one as the supervisor and the other one as the polishing operator. The system was trained with their faces with assigned authority levels prior to the test. The robot working area was limited to two horizontal planes workplane1 and workplane2 which covered the two areas mentioned previously. The robot shifts from workplane1 to workplane2 during the transition from task 1 to task 2. In task 1, the supervisor can start the operation and select a work piece to work on using SPR control system, and also drop vertically and close the gripper to pick up a short pipe which has been positioned vertically on a holder. In task 2, the operator can alter the position with their hand using DHMT control.

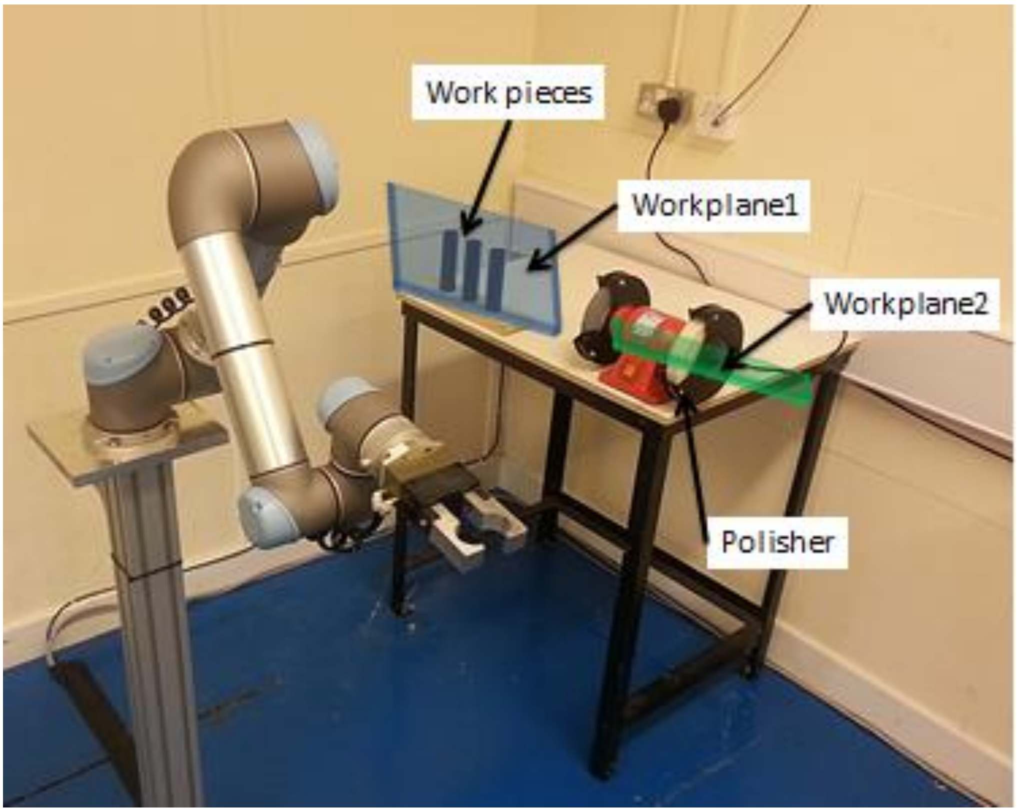


Figure 4-28 - the test bench consists of two working areas - component storage and polishing

The test began with the supervisor stepping into the control zone and starting the operation using the “start” gesture, the robot subsequently moved its gripper above the storage area and the supervisor has to use directive gesture commands to align the robot gripper with the component required before actuating the picking sequence by posing a “confirm” gesture. Once the component was successfully obtained from the component rack the robot moved the component above the polisher. At this point the supervisor passes control to the polishing operator. Once recognised by the system, the operator could then start the operation by closing their left fist and controlling the movement of the robot using DHMT control in front of the sensor. Once the component had been polished to a desirable level the operator closed their right fist, and the supervisor performed the “stop” gesture to indicate the end of the operation. The robot then dropped the component in a box and moved to a standby position. The test were carried out a number of times with successful results, the supervisors always being able to start operation, select a component using directive gestures and then pass control to an operator to carry out the polishing task. Using the DHMT control method, participants successfully made contact between the test components and the polisher. The purpose of this test was to illustrate the functionality of the system rather than as a real application but could be used when the operation required very large parts or operation in hazardous environment or with harmful materials.

The integrated system used one Kinect sensor as shared resource between the three subsystems which was occasionally affected by a known issue with the Kinect hardware driver. A bug with the hardware driver can cause the Kinect to disconnect from the computer when used as a shared resource between multiple programmes, but the problem can be solved by disconnecting and reconnecting the hardware. However, over 90% of the tests were not affected by this issue, and the issue can be fully solved by using one Kinect for each subsystem.

4.6 Development of an ergonomic and intuitive gesture control system

4.6.1 Introduction

This chapter describes the second iteration of the gesture control system development. In the second design iteration, more design considerations have been taken into account and these include design standards, ergonomics and human factor. The ergonomics and human factor studies are carried out exploratory studies illustrating how these methods can potentially be applied in future applications. A gesture control system was developed as a result of this design process. A demonstration has been carried out to show its potential application in human-robot collaborative task.

4.6.2 System architecture

The system consists of a small industrial robot with 6 degree of freedom (dof), control system with software written in C#, and a Leap Motion sensor. The Leap Motion sensor is used to capture user's hand gesture input and the control software processes the input and sends signals to robot controller. A decoder programme is created in the robot controller which receives signal from the control software through TCP server and actuate robot to perform actions (figure 4-29).

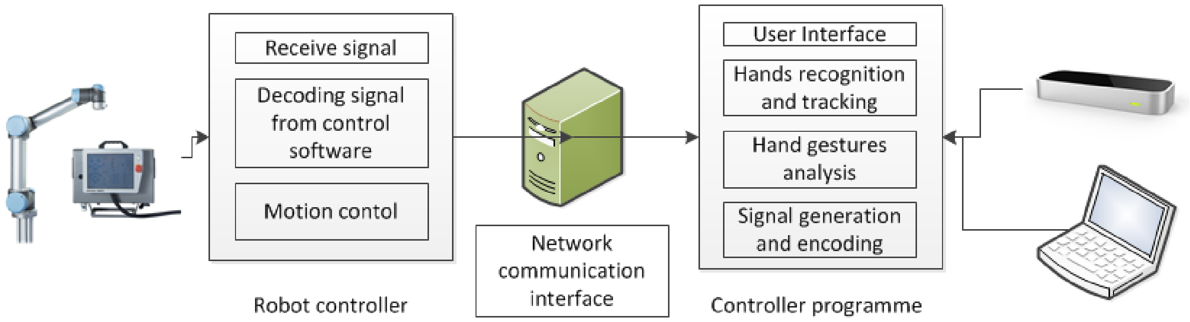


Figure 4-29 - system architecture

4.6.3 Standards

The BS ISO/IEC 30113-1 consists of a guideline for the design of gesture-based interfaces. The standard highlighted a number of requirements and recommendations and these include activating/ finishing a gesture, performing a gesture, feedback for confirming a gesture, feedforward, cancelling a gesture, criteria of gesture size, controlling the criteria, changing correspondence of a gesture command and descriptions of individual gestures within part. A number of these recommendations have been considered during the design of the developed system (British Standards Institution, 2015).

4.6.4 Gesture design process

The main design objective is to provide a natural user interface for user to take full motion control of robot without requirement of significant training. The natural user interface allow the operator to work with a comfortable posture, thus the risk of work-related musculoskeletal injury is reduced. One of the many causes of musculoskeletal disorders is the adoption of static or constrained postures. Using a control system may involve placing a load on the musculoskeletal system and discomfort, pain, fatigue will be influenced by the amount, duration and distribution of this load (Smith, 1996). Thus, a gesture control system designed to be used multiple times during a work shift should be designed in a way that reduces the risk to these injuries.

4.6.5 Gesture design constraints

Gesture is broadly recognised as a natural way of communication, but when designing gesture as machine input or control it is important to consider about constraints of technology and human.

Gesture control for robot motion should be continuous throughout the controlling period in which the user should be able to change the path of the robot immediately as intended. The robot movements need to be responsive so the user can receive an instant feedback to be assured the robot is operating according to the input, otherwise any delay in response will hinder movements synchronisation, and the user will feel disconnected to the robot. Thus the use of dynamic gesture recognition is prohibited, because a dynamic gesture routine typically takes over half a second to complete, so the system response is not instant. Therefore it cannot provide a continuous input to control the robot motion. The actuation method used in the developed system is based on hand positional thresholds so the robot responds as soon as user's hands reach the thresholds.

4.6.6 Technological constraint

Machines perceive human gesture through sensors and sometime processed using numerous algorithms, thus it is important to know the limitation of the technology to design a gesture control system that is reliable and robust to use. The developed system uses the leap motion as an input device. The device API provides tracking information of the user's hands which include the pitch, roll, yaw as well as the x, y, z positions relative to the sensor's centre point. The API can also recognise pinch or grab motions and return values between zero to one where one is a full pinch or grab, and zero is none. As explained previously, Leap Motion has certain amount of tracking errors which can be compensated by incorporating appropriate filters as demonstrated in (Du et al, 2015). However, the errors have remained relatively high compared to typical high-value production manufacturing tolerance (Jayaweera and Webb, 2007). This means that robot teleoperation involves mimicking human hand movement is technically challenging due to limitation of human motoring skills and current sensor resolution. However, the gesture input in this system is designed to actuate by hand positional threshold based on calibrated hands positions which is not affected by these limitations.

4.6.7 Human constraint

The senor tracks only the hand and finger movements, thus the posture analysis can focus on musculoskeletal movements involved in changing the hands' positions and orientations. The control hand movements are broken down into potential risks of musculoskeletal injury. For instance, changing the hands' pitch, roll and yaw require wrist flexion, radial deviation and ulnar deviation respectively (figure 4-30). Changing the x, y, z position of the hand requires upper arm movement or lower arm movement and sometimes both. When designing a control system, these required body movements should be identified and the implication on health should be assessed.

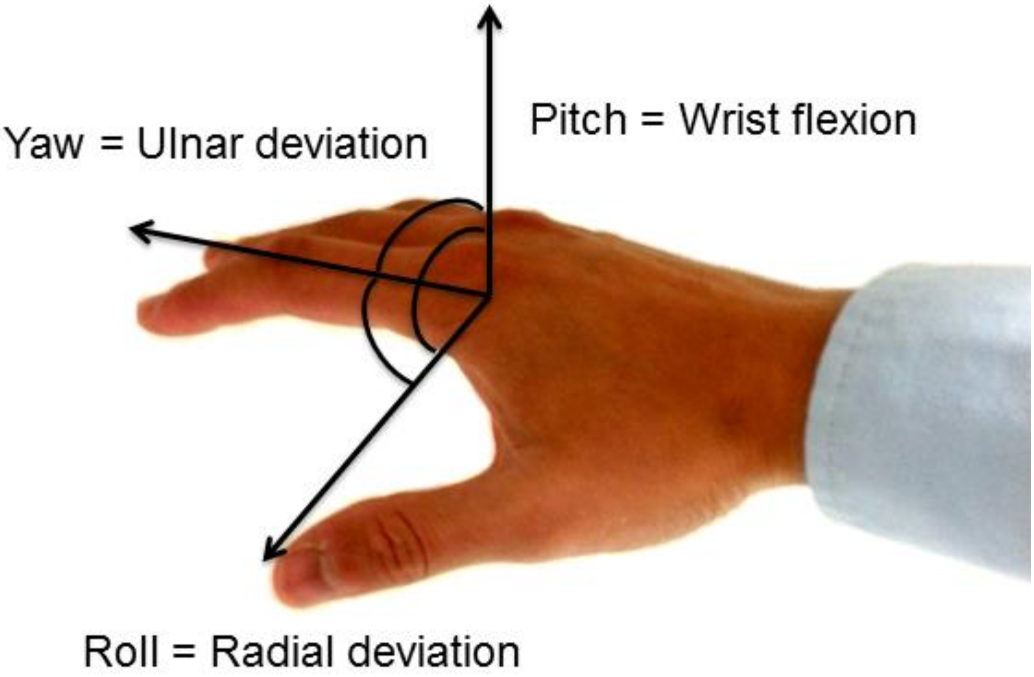
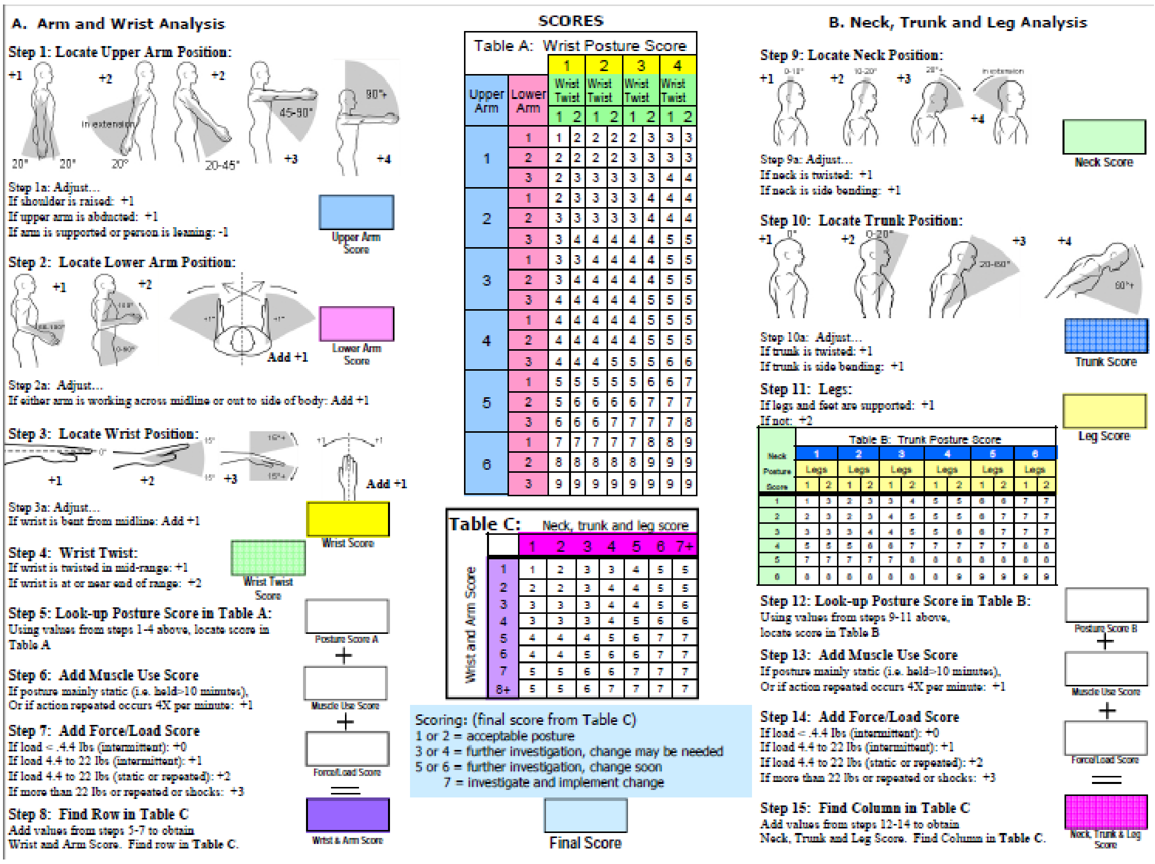


Figure 4-30 - Wrist movements and changes in sensor values

The Rapid Upper Limb Assessment (RULA) (McAtamney and Corlett, 1993) postural analysis is chosen to aid the design of gestures and assess the risk of musculoskeletal injury associate with the system usage. It is an effective method for assessing the risk level of task requires movement of the upper limbs. The tool is chosen based on its simplicity and reliability compare to other assessment methods (Kee and Karwowski, 2007).

The RULA assessment method (figure 4-31) is used in the assessment of human constraint during the system design phase. The assessment has a score system with two parts which include part A: Arm and Wrist Analysis and Part B: Neck, Trunk and Leg Analysis. The scores accumulate at each step and the final score is calculated using a combination of three score tables.

The Arm and Wrist Analysis indicates that the upper arm position should stay within +/- 20 degree from the vertical axis or the score increases. A raised shoulder or abducted arm also increases the score which should be avoided. The lower arm position should stay within 60-100degree from the vertical axis otherwise the risk increases. Any deviation of the lower arms from the midline of the body will increase the risk, but it is inevitable if one of the hand positions is required to change in the x-axis of the sensor. Wrist flexion within +/-15 degree will add two points, but any movement over the range will add three points. Any ulnar deviation will add another one point to the score, but it is avoidable by using lower arm movement instead to change hand yaw in sensor values. Wrist twist within midrange will only add one point to the wrist and arm score. Finally, highly repeatable posture or prolonged static posture will increase the risk as well as added force or load larger than 4.4lbs on the hand. The developed system has received minimum risk score from the Neck, Trunk and Leg Analysis as it is design to be used in comfortable standing posture as described in BS EN ISO 9241-5:1999 (British Standards Institution. 1999).



A. Arm and Wrist Analysis

Step 1: Locate Upper Arm Position:

Step 1a: Adjust…
If shoulder is raised: +1
If upper arm is abducted: +1
If arm is supported or person is leaning: -1

Step 2: Locate Lower Arm Position:

Step 2a: Adjust…
If either arm is working across midline or out to side of body: Add +1

Step 3: Locate Wrist Position:

Step 3a: Adjust…
If wrist is bent from midline: Add +1

Step 4: Wrist Twist:
If wrist is twisted in mid-range: +1
If wrist is at or near end of range: +2

Step 5: Look-up Posture Score in Table A:
Using values from steps 1-4 above, locate score in Table A

Step 6: Add Muscle Use Score
If posture mainly static (i.e. held>10 minutes),
Or if action repeated occurs 4X per minute: +1

Step 7: Add Force/Load Score
If load < .4.4 lbs (intermittent): +0
If load 4.4 to 22 lbs (intermittent): +1
If load 4.4 to 22 lbs (static or repeated): +2
If more than 22 lbs or repeated or shocks: +3

Step 8: Find Row in Table C
Add values from steps 5-7 to obtain
Wrist and Arm Score. Find row in Table C.

SCORES

Table A: Wrist Posture Score

		1		2		3		4	
		Wrist Twist		Wrist Twist		Wrist Twist		Wrist Twist	
Upper Arm	Lower Arm	1	2	1	2	1	2	1	2
1	1	1	2	2	2	2	3	3	3
	2	2	2	2	2	3	3	3	3
	3	2	3	3	3	3	3	4	4
2	1	2	3	3	3	3	4	4	4
	2	3	3	3	3	3	4	4	4
	3	3	4	4	4	4	4	5	5
3	1	3	3	4	4	4	4	5	5
	2	3	4	4	4	4	4	5	5
	3	4	4	4	4	4	5	5	5
4	1	4	4	4	4	4	5	5	5
	2	4	4	4	4	4	5	5	5
	3	4	4	4	5	5	5	6	6
5	1	5	5	5	5	5	6	6	7
	2	5	6	6	6	6	7	7	7
	3	6	6	6	7	7	7	7	8
6	1	7	7	7	7	7	8	8	9
	2	8	8	8	8	8	9	9	9
	3	9	9	9	9	9	9	9	9

Table C: Neck, trunk and leg score

Wrist and Arm Score		1	2	3	4	5	6	7+
	1	1	2	3	3	4	5	5
	2	2	2	3	4	4	5	5
	3	3	3	3	4	4	5	6
	4	3	3	3	4	5	6	6
	5	4	4	4	5	6	7	7
	6	4	4	5	6	6	7	7
	7	5	5	6	6	7	7	7
	8+	5	5	6	7	7	7	7

Scoring: (final score from Table C)
1 or 2 = acceptable posture
3 or 4 = further investigation, change may be needed
5 or 6 = further investigation, change soon
7 = investigate and implement change

B. Neck, Trunk and Leg Analysis

Step 9: Locate Neck Position:

Step 9a: Adjust…
If neck is twisted: +1
If neck is side bending: +1

Step 10: Locate Trunk Position:

Step 10a: Adjust…
If trunk is twisted: +1
If trunk is side bending: +1

Step 11: Legs:
If legs and feet are supported: +1
If not: +2

Table B: Trunk Posture Score

Neck Posture Score	1		2		3		4		5		6	
	Legs		Legs		Legs		Legs		Legs		Legs	
	1	2	1	2	1	2	1	2	1	2	1	2
1	1	3	2	3	3	4	5	5	6	6	7	7
2	2	3	2	3	4	5	5	5	6	7	7	7
3	3	3	3	4	4	5	5	6	6	7	7	7
4	5	5	5	6	6	7	7	7	7	7	8	8
5	7	7	7	7	7	8	8	8	8	8	8	8
6	8	8	8	8	8	8	8	9	9	9	9	9

Step 12: Look-up Posture Score in Table B:
Using values from steps 9-11 above,
locate score in Table B

Step 13: Add Muscle Use Score
If posture mainly static (i.e. held>10 minutes),
Or if action repeated occurs 4X per minute: +1

Step 14: Add Force/Load Score
If load < .4.4 lbs (intermittent): +0
If load 4.4 to 22 lbs (intermittent): +1
If load 4.4 to 22 lbs (static or repeated): +2
If more than 22 lbs or repeated or shocks: +3

Step 15: Find Column in Table C
Add values from steps 12-14 to obtain
Neck, Trunk and Leg Score. Find Column in Table C.

Figure 4-31 - RULA Employee Assessment Worksheet

The RULA assessment is the core of the human-centred design process of this development. The human constraints highlighted from the assessment are considered at the initial gesture design stage as well as each design iterations. It was established at the beginning that in order to achieve intuitive gesture control the user’s hands will be moving within a Cartesian space and some wrist flexion movement will be required. In this case, the threshold for low risk hands movements can be calculated using the joint angles provided in RULA.

The Leap Motion sensor will be positioned flat on a solid surface and in front of the user as it is originally intended. The x,y,z positions of one of the user’s hand will be used to actual control input which require shoulder and elbow joint movements. It is know from the assessment that both joints should not require to move over +/-20 degree from a default position. Using this information combined with anthropomorphic data the ideal sensor height, working area and threshold for actuation are calculated.

Figure 4-32 is a model in the operating posture, labelled are the parameters used in the calculation for the system setup. Maximum joints movement angles for low risk classification are obtained from the RULA assessment. Limb lengths can be obtained from national anthropomorphic data according for use in different region.

The sensor height Hs is calculated using the elbow height He, the neutral lower position angle $\theta\mathrm{en}$, the elbow to fingertip length EF and the ideal hand to sensor height Hhs which can be expressed as:

$$\tan \theta\mathrm{en} \cdot EF + Hhs = Hs \tag{1}$$

The lower arm movement threshold Mla is calculated using the elbow to fingertip length EF and the maximum low risk elbow joint angle $\theta\mathrm{e}$ which can be expressed as:

$$\frac{\theta\mathrm{e}\pi}{180} \cdot EF = Mla \tag{2}$$

The upper arm movement threshold Mua is calculated using the shoulder to elbow length SE and maximum low risk shoulder joint angle $\theta\mathrm{s}$ which can be expressed as:

$$\frac{\theta s \pi}{180} \cdot SE = Mua \tag{3}$$

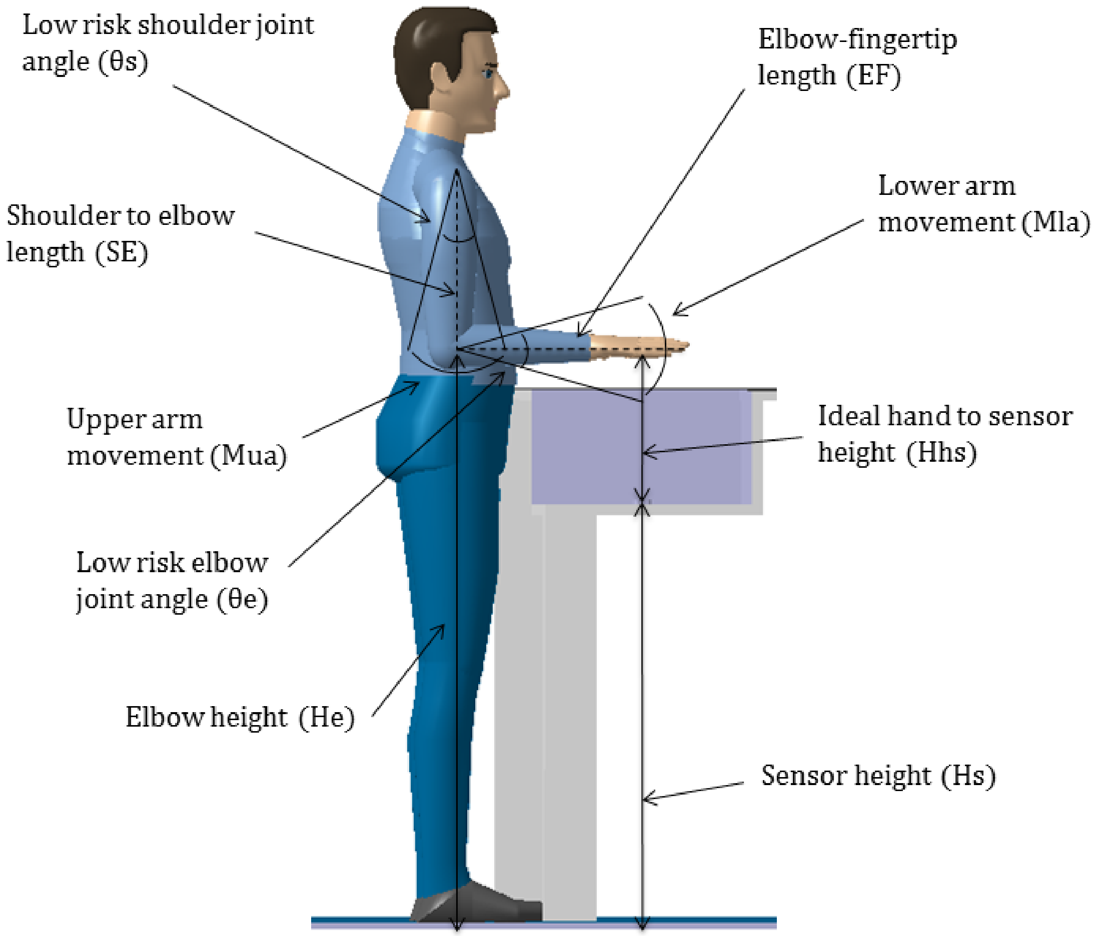
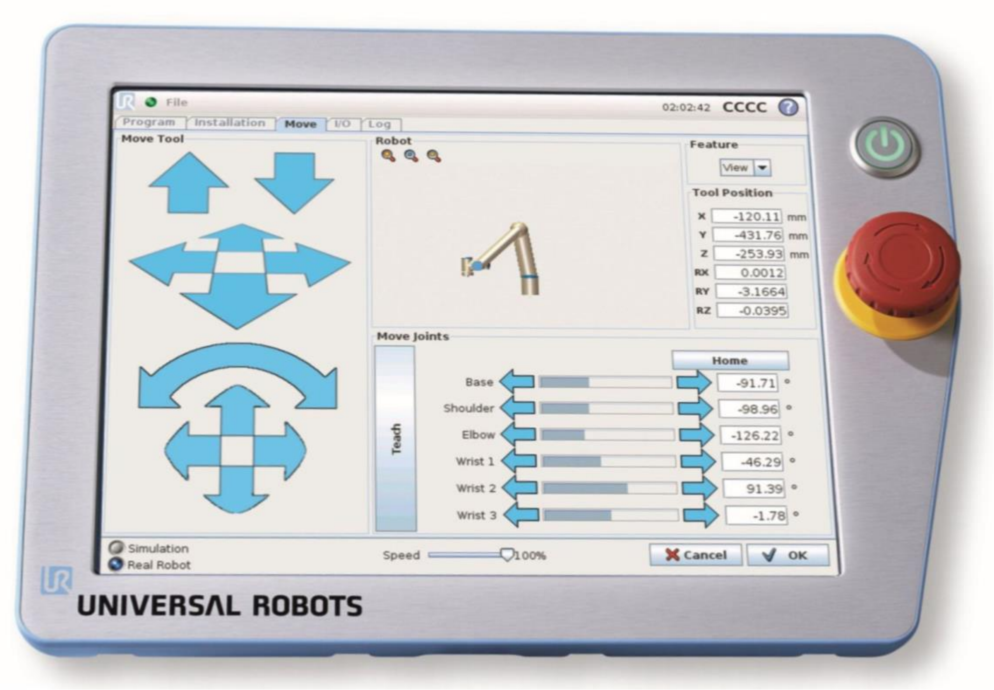


Figure 4-32 - model showing the upper arm constraint

4.6.8 Robot control

The robot in the system is a small industrial articulated-arm robot with 6 DOF. This layout is one of the most common layouts for industrial robot due to its high degree of freedom, relatively large working envelop, flexibility and adaptability to numerous applications, and the acceptable repeatability. The robot used in the testing has six joints which include base, shoulder, elbow, wrist1, wrist2, and wrist3. Like most robot, the movement of the robot is controlled using a teach pendant as shown in figure 4-33. The teach pendant allows the user to alter the position of each individual joint on the robot, as well as the tool centre point

(TCP) in Cartesian coordinates. The developed system allows user to control robot movement without the use of the teach pendant. As mentioned in Hands and fingers tracking, the Leap Motion Sensor and API can accurately track the user's hands Cartesian position relative to the device's origin as well as the pitch, yaw, and roll of both hands. The API can also track pinch or grab motion of both hands. The control software uses these tracking data as input for mode change, actuation and robot control.



X -120.11 mm
Y -431.76 mm
Z -253.93 mm
RX 0.0012
RY -3.1664
RZ -0.0395

Base -91.71 °
Shoulder -98.96 °
Elbow -126.22 °
Wrist 1 -46.29 °
Wrist 2 91.39 °
Wrist 3 -1.78 °

Speed 100%

Figure 4-33 - the Universal Robots teach pendant

The control software is designed to enable the user to control the motion of the robot, but unlike some of the gesture control systems described in literatures this system enable user to control the movement by joint and movement in Cartesian space. This is achieved by separating different control methods into modes and user can navigate through the list of modes to complete different movements. The developed software consists of the Joint mode and Cartesian mode. In Joint mode, the user can take control of the robot's base, wrist1, wrist2, and wrist3. The Cartesian mode enables user to change the x, y, and z position of the robot's TCP (figure 4-36). The user can switch between modes by performing a pinch gesture with their left hand. The list of modes, functions and triggers are shown in table 4-7. The level of control is expandable to include rotational movements and other joint movements, but the range of control is limited at this stage of development for the ease of use.

Table 4-7 - user input and robot control mode

Mode	**Function**	**Trigger**
Off	No movement	None
Joint	Base movement	Left hand roll threshold
Joint	Wrist 1 movement	Right hand pitch threshold
Joint	Wrist 2 movement	Right hand yaw threshold
Joint	Wrist 3 movement	Right hand Roll threshold
Cartesian	Movement in X axis	Right hand X threshold
Cartesian	Movement in Y axis	Right hand Y threshold
Cartesian	Movement in Z axis	Right hand Z threshold

The system identifies an input by constantly monitoring the values of hands tracking module. If a particular value meets its threshold then the programme identifies it as a user input and generate appropriate signal to the robot controller. Each input has its own threshold, for example the pitch of the right hand has to reach a certain degree before an input is triggered as illustrated in figure 4-34. These thresholds are defined according to the results from the calculations described in Human constraints.

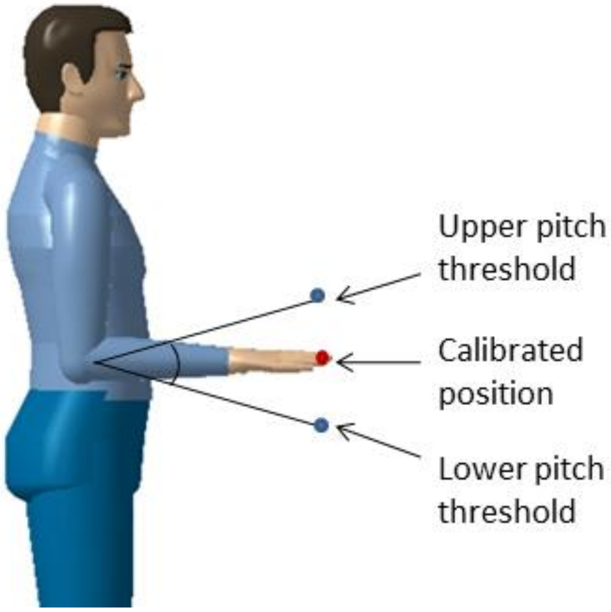


Figure 4-34 - hand position and pitch thresholds

The control PC communicates with the robot controller via TCP/IP network. The control software sends encoded signals to the robot controller and a decoder within the robot programme interpret the signals and drives the robot according to the input. Each encoded signal is an array which contains variables representing the movement mode, joints speeds, velocity vectors and rotation angles. The robot controller decoder interprets this array and set the speed of the robot depending on the mode of movement and directional values. For movements in Cartesian space, the controller set the speed in the format of (x, y, z, α, β, γ) where (x, y, z) represent the linear movements and (α, β, γ) represent the rotation movement about the x, y, z axes. For movements joint, the controller set the speed in the format of (joint 1, joint 2, joint 3, joint 4, joint 5, joint 6). The robot movement is configured according to the acceleration, speed and response time of the robot

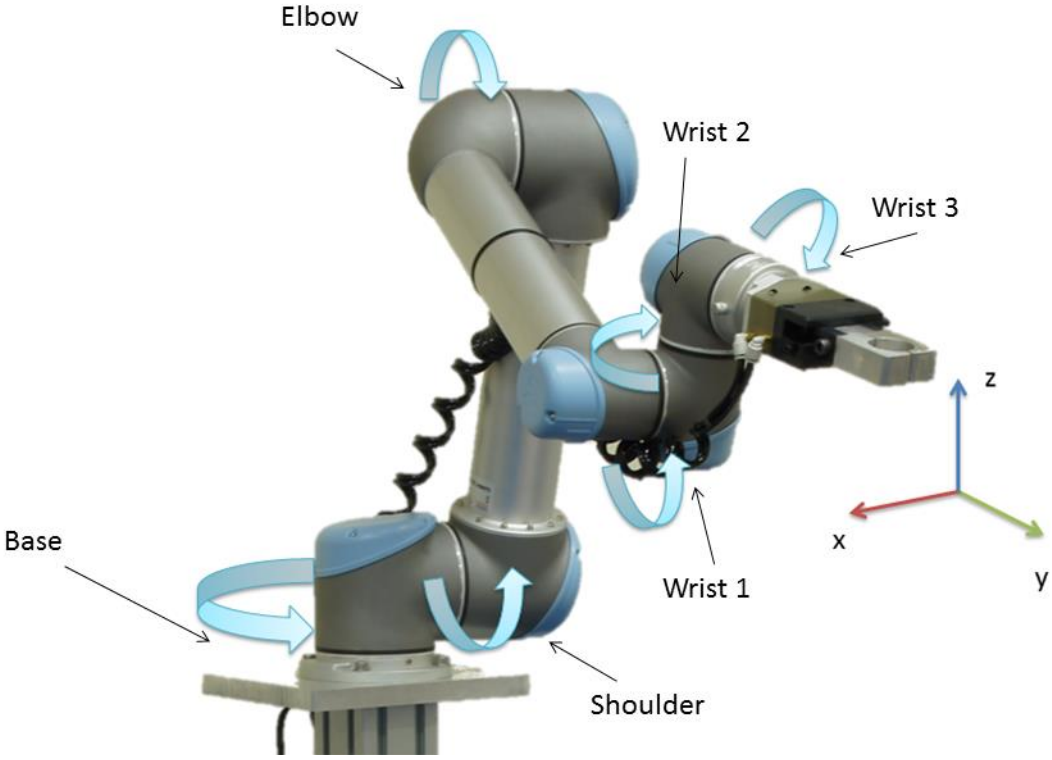


Figure 4-35 - the Universal Robot UR5 has 6 dof which can be utilised with the gesture control system

The hands positions is stored in temporary memory when changing from mode 0 to mode 1 for calibration of the hands, and this occurs every mode change cycle. The purpose is to enable every user to use the system in their most comfortable position, because people have varied natural position of the wrists, and therefore the degrees of radial deviation and flexion of the wrists will also vary. The design of this control system is to ensure the user interface is intuitive to use without the requirement of significant training and the user can produce input with natural hand movements.

4.6.9 Safety and Robustness

A number of characteristics of the system have been design purposely to increase the robustness of the system and improve system safety. For example, the robot movement is progressive and the speed is limited to teach mode level so user should notice any abnormal movement of the robot and react to it. The control programme can only operate when both hands are present above the sensor, if the user lift one or both hands away from the sensor then the robot will stop immediately. The system also features an “Off mode” for when the system is not being used and this feature avoid false trigger by movements near the sensor.

A simple graphical user interface has been designed to provide information about robot mode and the hands tracking state of the programme as shown in figure 4-36. An image of a pair of hands appears when both hands are detected above the sensor. Directional arrows become visible when user’s hands go above or below any positional thresholds. This enables user to be certain that the robot is engaged in the most appropriate mode as well as the status of the hand tracking module. The interface is shown on a pc monitor in front of the sensor and the user.

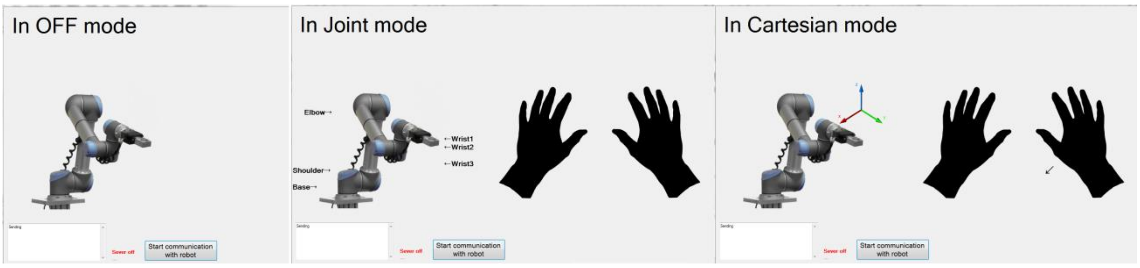


Figure 4-36 - user interface in different modes

4.6.10 Usability of the Leap Motion Gesture Control system

The evaluation of the contactless robot control system is described in this section. Traditionally the motion of a robot manipulator is controlled using a teach pendant. However, in a human-robot collaborative environment a more effective and intuitive way of communicating to the robot is required. A contactless gesture system can provide a more natural way of controlling the robot motion for the user. Using gesture input, the user can control the robot by relating their hand motions to the movements of the robot which also reduce physical workload. The experiment aims to identify area of improvement for the developed contactless gesture control, and to compare its user experience with a modern robot teach pendant.

A comparison study has been carried out at the development stage to compare the risk of using the developed system against a touch screen teach pendant using RULA. RULA has a final score scale from one to seven where a final score of one to two mean the posture is acceptable, three to four means change may be needed, five and six require further investigation and change required soon, and a score of seven leads to investigation and implement change.

Eight people from the general population of Cranfield University have participated in the usability experiment. Four of them were males and four of them were female, and all participants were right-handed. Their age ranged from 23 to 51 years with mean of 30 (SD = 9.27). Five of the participants have some experience in robot control and three of the participants are inexperienced robot operators. Each experiment took around 35 minutes.

The gesture control system has been tested with a Universal Robot UR5 robot. The UR5 features a modern teach pendant with touch-screen and graphical user interface (GUI). Each experiment starts with a five minutes brief about the basic of industrial articulated robot with 6 dof which covers motion control techniques. Before the test of each control interface, the participants were given a five minutes training and practicing period. The actual testing time of each system last approximately 10minutes, participants were given the option to take a five minutes break after testing the first system before continuing to the second test. Each participant was asked to fill out a system usability questionnaire (SUS) (Brooke, 1996) immediately after each test. Participants were asked to score the system against five criteria which include tiredness from using the system, ease of use, intuitiveness, enjoyableness and the ability to perform action as intended. These criteria are similar to those described by Bhuiyan and Picking (2011), but the questionnaire used in this test was simplified. Each criterion is assessed based on a seven point scoring system where seven is positive and zero is negative. The purpose of the questionnaire is to measure their experience of using the system. Each participant uses both systems in the experiment which introduces the risk of a carryover effect. This is prevented by having alternated testing orders for the two control interfaces.

Three pipes are positioned in front of the robot on stands. The participants were given the choices to attempt positioning the robot gripper onto the pipe in a position to grab the pipe. The gripper was not activated and the manipulation task was given simply to provide a goal for the participants to make use of the control systems. The task was not part of the test.

4.6.11 Results

In the RULA test a higher score indicates an increased risk of musculoskeletal injury after prolonged usage. In this particular assessment gesture control scored three points and teach pendants scored four points. The score of the teach pendant can further increases if the device weights over two kilograms. It was identified that the wrist movement in Leap Motion Robot Control poses the biggest problem in terms of posture, but the risk is relatively insignificant. The analysis highlighted potential issue with the neck when using a teach pendant, because its operating angle suggests a high load which could lead to musculoskeletal discomfort when used for prolonged periods. Furthermore, the lower arms have to be raised to a significant angle when using a teach pendant which may cause tiredness after a long period of usage. It is also found that prolonged usage of a teach pendant cause tiredness in the wrist of the hand holding the teach pendant.

The usability experiment results are presented in figure 4-37. Two participants verbally reported it was tiring to hold the robot teach pendant during the test which lead them to leave the device on the worktop in majority of the test. However, in the questionnaire they have provided a positive score for the level of tiredness which were contradictory. Thus, their results were deemed as inaccurate and discarded.

The results shows that participants generally find gesture control less tiring to use compared to the conventional teach pendant, the mean score were 3.83(SD=0.75) and 3.33(SD=1.03) respectively. Gesture control has also received higher score than teach pendant for intuitiveness 4.5(SD=0.84) and 4.33(SD=1.03). People also found the gesture control to be more enjoyable to use compare to the touch screen teach pendant, the mean score were 5.67 (SD=0.52) and 5.33(SD=0.52) respectively.

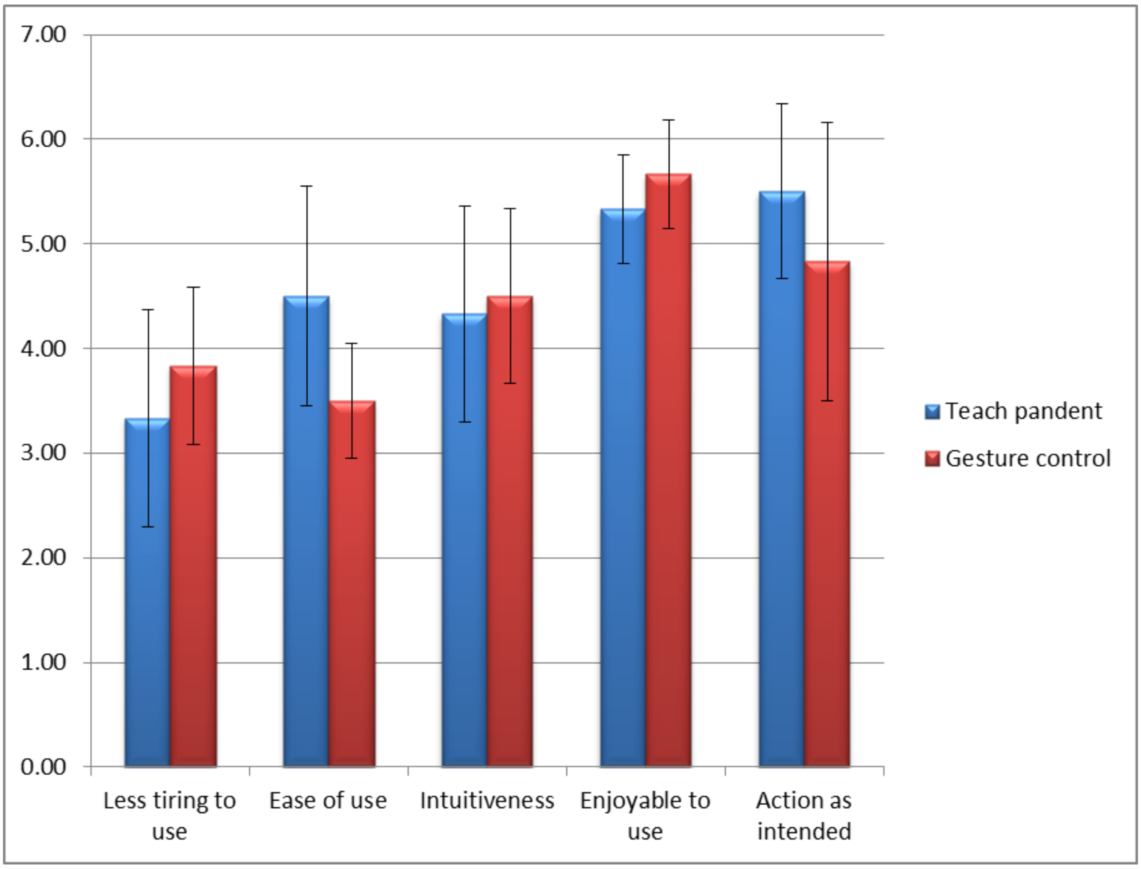


Figure 4-37 - mean ratings given to the two systems in five criterions, error bars = SD

The teach pendant scored higher for ease of use and action as intended, the reasons were reflected in the semi-structured interview. Most participants have reported the visual feedback of the GUI and the touchscreen have made it easier to use, which indicates the potential benefit of incorporating visual feedback and tactile feedback into gesture control system. Several participants have experienced confusion with the spatial orientation using gesture control, particularly when moving in Cartesian space. The participants relate the robot arm to their own body. For example, they believe moving their hand away from the body would cause the robot's TCP to move away from the base. Participants have reported similar issues with the teach pendant although their working position is correct with the robot's orientation. Half of the participants reported that the teach pendant is heavy to hold. Some participants experienced difficulty to find the thresholds in gesture control which led to a delay in robot response. A GUI was presented in front of the participant to indicate the tracking status and the robot movement actuated, but most participants appear to be distracted by robot movements and fail to check the visual status. This aligns with the findings of (Tenbrink et al, 2002; Moratz et al, 2001). 50 percent of the participants reported that the teach pendant is heavy to hold. Some participants experienced difficulty to find the thresholds in gesture control which led to a delay in robot response.

4.7 Integration of gesture control with a heavy duty industrial robot

4.7.1 Introduction

This thesis investigates the integration of gesture control with a traditional industrial robot. These robots were designed for performing highly repetitive manufacturing task with typical repeatability of better than ±0.01mm and payload capability of up to over 800kg. However, these heavy duty robots were mainly designed to operate in isolation from human. Thus, extra care must be taken in terms of work cell setup, control configuration and safety of human operator. This chapter discusses the integration of a static pose recognition type gesture command system with a Comau NM-45 industrial robot. The control of the robot is being carried out using the original C4G controller, because this setup enables the robot to retain all of its original functions. In this case, the gesture control system is integrated as a secondary control device.

4.7.2 Robot setup and safety

An industrial robot system shall be integrated according to the ISO 10218-2:2011. For collaborative applications, the robot cell should be monitored using safety monitoring systems and the human must be separated from the robot by a safety distance during an automatic operation. The safety distance can be calculated using the safety distance formula provided by the standard of safety of machinery EN ISO 13855:2010 as described in chapter 2.9.

In this system, the Comau NM-45 robot has 45kg payload capability and approximately 2m reach. For safety reason, the maximum speed of this setup has been restricted to a teach mode speed of 500mm/s. Using this maximum speed, a safety distance has been calculated to be approximately 2.5m. The end-effector is a Robotiq intelligent gripper for grasping objects. The open and close operations of the gripper are driven by the robot controller. The work cell is monitored using safety light curtain and laser safety scanner as the secondary device which means that it is a fail-safe system. The monitoring area is defined by the safety distance from the robot as illustrated in figure 4-38 highlighted by the dotted lines.

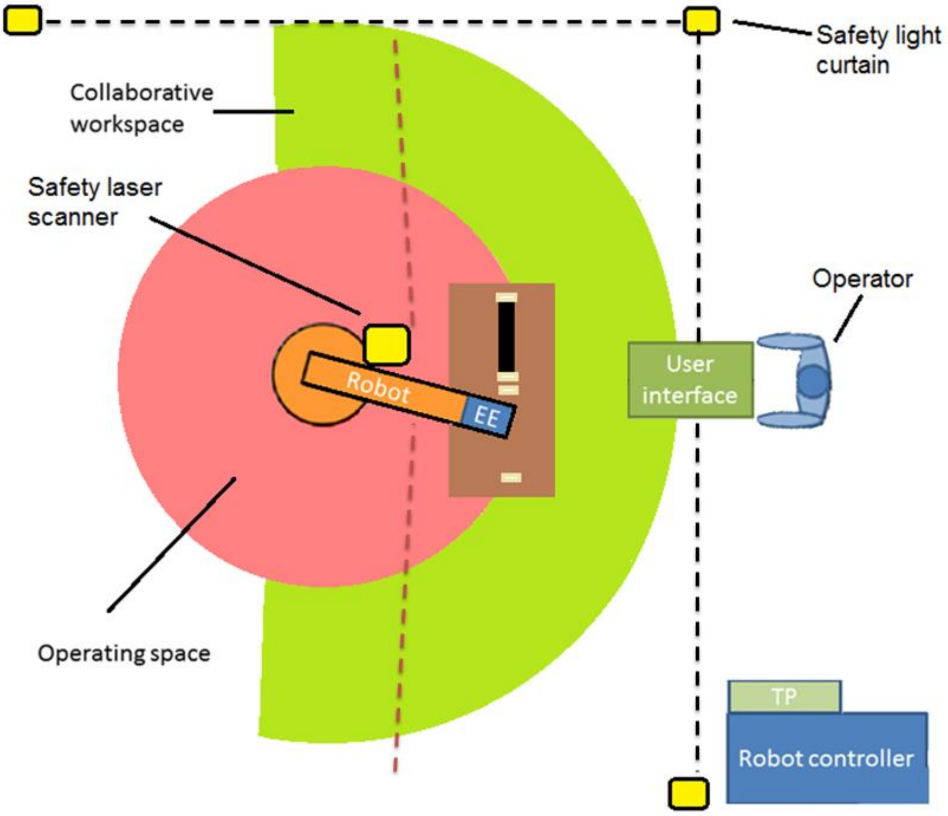


Figure 4-38 - industrial robot collaborative cell layout; EE=End-effector, TP=teach pendant

The operator must be standing outside the robot operating area separated by a safety distance. Thus, for demonstration purposes the gesture user interface is positioned just outside the collaborative space.

The gesture user interface tracks the user’s hands using a Leap Motion sensor which enables the user to make command through hand and wrist movements. The principle of the gesture commands is similar to the system described in chapter 4.6, but the functionality and system structure are different from the Universal Robot UR5 integration which is due to the differences in the controller programme structure as explained in the next chapter.

4.7.3 System structure

As explained in chapter 3.8, many industrial robot controllers do not feature multi-threading architecture and the Comau C4G controller is one of them. However, processing gesture command is achievable in sequential programming. In this case, the robot programme is structured into three separated modules which are illustrated in figure 4-39. The main programme operates as the central control in this architecture which activates other sub-programme when required. The interface programme communicates with the gesture command system which receives and decodes incoming variables. The action programme runs pre-programmed movement routines when it receives assignments from the main programme. The routine is selected depending on the incoming command.

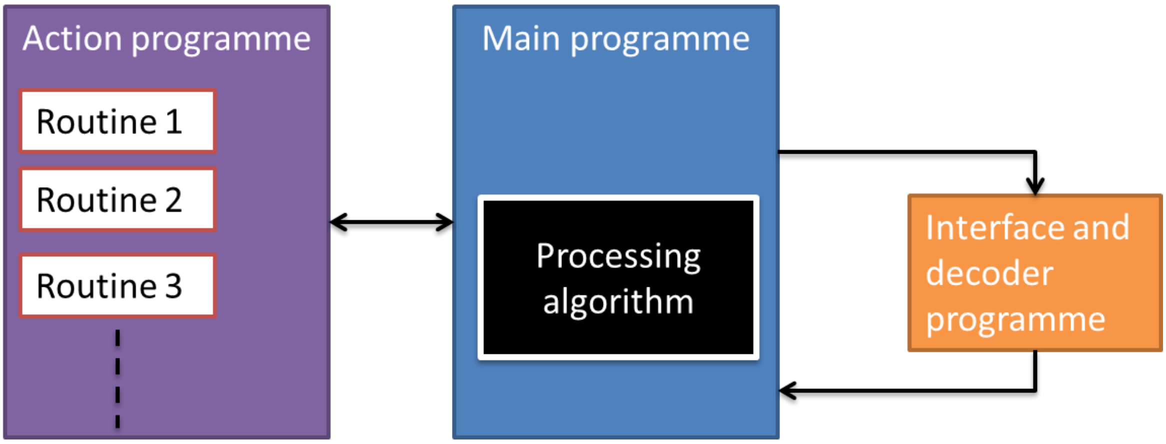


Figure 4-39 - robot programme structure

Using this method, the user can control the robot to perform a range of manipulative movements using hand gestures.

4.7.4 Demonstration

A demonstration was created to validate the capability of the gesture control on the Comau NM-45 robot. For simplicity, a pick-and-place task was selected for this demonstration. The aim of the task is for the user to command a robot to pick up a piece of plastic pipe which is rested on a set of holders, and then drop off the pipe onto another set of holders. The gesture control is a single handed system which is operated by the user tilting their hand to appropriate directions.

The gripper can be operated by the closing palm motion of the user, closing palm once will close the gripper and closing again will reopen it. The robot working area is segregated into zones as illustrated in figure 4-40 and the robot moves to different zones according to the user's gesture command. For example, if the user wishes to move the robot from zone 1 to zone2, they would tilt their hand downwards. However, the robot will only move according to a set of rules designed of this task to avoid unexpected events. For instance, when the robot is in zone 2 it will only accept the "up" command to move to zone 1. If the user attempts to command the robot to move from zone 2 to 3 or 4, the robot will ignore the command.

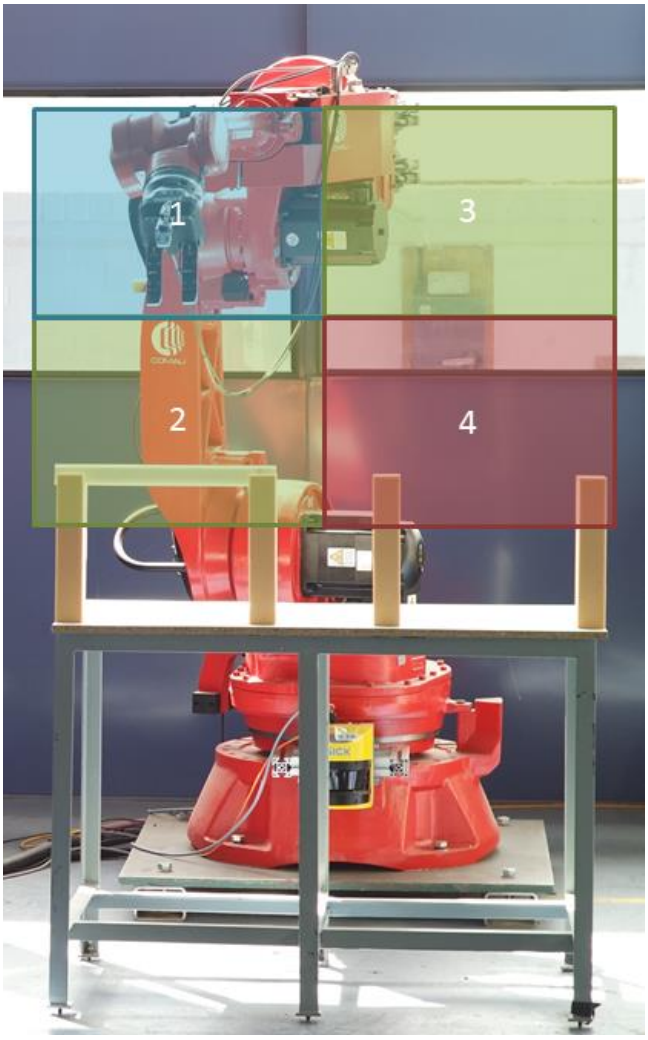


Figure 4-40 - gesture control movement zones

The task begins with the robot in position 1, the operator should tilt their hand downwards to move robot into position 2. Once reached position 2, the operator can close their palm once to close the gripper which will hold the pipe. At this point, the operator should tilt their hand upwards to indicate moving back to the first position, which follows by tilting to the right for the robot to move to position 3. Finally, the operator can tilt their hand downwards to move to the final position. The gripper will release the pipe when the operator performs the closing palm motion. The four robot positions are shown in figure 4-41. This demonstration has been carried out for 20 times with 100% success rate.

Figure 4-41 - gesture controlled Comau NM-45 industrial robot

4.7.5 Conclusion

This chapter has described the integration of a gesture control system with a heavy duty industrial robot. A gesture controlled robot pick-and-place task was successfully demonstrated with this system. The aim of this chapter is to highlight some of the technical challenges when carrying out this type of integration, but also to illustrate potential applications with gesture interface. It is possible to apply this system on some real industry applications. One of the potential applications is robot manipulation of large components. For example, an operator can direct a robot manipulation of a heavy part using hand gestures which allows the operator to conveniently enter the collaboration area to perform manual task on the large component and readjust position when required.

5 Robot to human communication

A human-robot collaborative manufacturing system may require frequent interventions by human operators. In this case, effective communication is paramount for smooth operations. Traditional factory machines communicate with human users through visual and audible signalling. Manufacturing plants are complex environment with numerous background noises varying from human voice to audible signals to collisions and abrasions of metals, which minimises the effectiveness of audible indication. It is often required that human workers are not wearing any additional devices, and therefore this has prohibited the use of wearable notification devices.

Many human-machine interface developments are technology-focused where subsystems were developed to perform each function with a display for each system that informs the operator of its present status. A human-robot collaborative system designed solely based on a technology-centred approach can have a negative effect on the user performance, which can cause design-induced errors (Boy, 2012). Due to the information processing bottlenecks of humans, people can only pay attention to a limited amount of information at once. As the display of data in these systems is designed based on the technologies producing them, it is often arranged in a way that is not ideally suited to support human tasks. Thus, extra mental capacity is needed to extract useful information which ultimately leads to higher than necessary workload and error. By applying the philosophy of user-centred design a more effective collaborative system is achievable. User-centred design challenges designers to build a human-robot interface around the capabilities of the potential users. A user-centred design also improves user acceptance and satisfaction as a side benefit (Endsley, 2011).

This chapter describes a number of approaches and experiments which are summarised in table 5-1:

Table 5-1- summary table of development in chapter 5

Communication type	**Name of concept**	**Description**	**Experiment**
Robot communicative gesture motion	Robot gesture	This exploratory study investigates the feasibility of using gesture motions performed by an industrial robot to communicate with its users	An experiment was carried out to study the effect of robot gestures on users' understanding and trust
Signal lights	Robot light skin	This thesis proposes the concept of using a light-emitting skin on a robot for communication with users during collaboration	An experiment was carried out to compare the robot light skin against a conventional tower light in terms of users' reaction time, workload and awareness

5.1 Signal communication between machine and human

When designing a communication system for human-robot collaborative working, it is important to consider how humans perceive signals in order to develop an effective system. In an industrial human-robot collaborating scenario, an operator can be carrying out a manual task whilst monitoring one or more robots. The robot in this case may signal to the operator for a request of cooperation. In this instance, the signalling system needs to catch the operator's attention when they are focusing on a different task. Human react involuntarily to salient events as well as paying attention to things which are relevant to their current activity. Visual attention resulting from saliency effects in terms of changes in contrast, size or colour are referred to as bottom up (Northdurft, 1993; Taylor and Stein, 1999).

In conventional industrial settings, tower lights are commonly used for visual signalling of factory production cells. Small assembly lines or cells are often operating in parallel with one tower light placed above the last station along the transportation aisle indicating the state of operation. The main benefit of tower lights with red, yellow and green lights is a simple and effective communication tool which allows managers and supervisors to be aware of the state of production lines at a glance (Baudin, 2002). However, when applied on a human-robot collaborative production system the visual signal becomes a means of communication with the human operator to indicate any system error or request for interaction. Tower lights are also known as Andon lights in the context of visual management which supports Lean production system. Andon lights are aspects of the Jidoka principle. Jidoka is a manufacturing term which refers to principle of stopping work immediately when a problem occurs. An Andon light can provide visual signals to indicate the present of wastes in a factory, which are the main source of potential improvements in business performance. An effective visual signalling system ensures that an appropriate response to an event can be made on time, every time by everyone involved (Subramaniam et al, 2009). This type of lighting system is also used in Visual Management which is a lean tool based with the goal to create a status at a glance in the workplace. This refers to a factory environment where anyone can enter the workplace and see the current situation, see the work process, see the progress and see when an abnormality occurs (Greif, 1991).

Tower lights are widely used not only in manufacturing environments, but also in everyday life situation such as supermarket self-checkout. Each self-checkout counter is equipped with one tower light which is usually positioned above the machine to indication whether it is in normal working order or when attention is needed. In the event of an error occur, the tower light change from green to red to indicate human help is needed, and a contact staff will approach the machine when they notice the signal. In this case, the response time of the contact staff is largely depended on the ease of noticing this visual signal (Anıtsal, 2005; Schatz, 2003; Orel and Kara, 2014).

In a human-robot collaborative production system, the robot can be operating as an intelligent assistant which assists the human operator in some way while the operator is carrying out a different task. Due to the variable nature of the operating environment the robot system may detect an abnormality which requires decision making by the human operator. In this case, visual signals can be one of the forms of interface between the robot and human. However, the problem of a traditional tower light is the restriction on placement which is usually outside the robot's working envelop. If positioned inside a robot's working zone or on the robot arm it may reduce the overall system flexibility due to the physical properties of the tower light, and the signal can be hidden from view by robot movement. The aim of this research is to develop an indication system specifically designed for collaborative robots which enables the operator to react promptly to a robot signal during a manufacturing operation.

Furthermore, the operator of a collaborative system can be working on a demanding manual task while paying attention to robot action to ensure smooth operation. In this case, it is logical to minimise the number of objects which require visual attention. Humans in general have limited capacity in paying attention to multiple events, people withdraw from some things in order to process effectively with others (James, 1913). Thus, the developed system should not distract the operator's sight away from the robot. Industrial tower lights are typically fixed at a location near the machine, and operators have to draw their visual attention to the light unit to see a change of light. This is an example of top-down spatial attention where the subject can assign their attention to a small region of space within their field of view (Pinto et al, 2013). However, research evidences have shown that top-down attention appears to take longer to deploy than bottom-up attention (Cheal et al, 1991; Hein et al, 2006; Ling and Carrasco, 2006; Liu et al, 2007; Muller and Rabbitt, 1989). Thus, the developed system should be integrated on the robot to provide dynamic visual signals which can be captured by users using bottom-up attention.

There are a number of studies on human-robot interaction through visual signalling in the context of social and mobile robots, but little research can be found in industrial human-robot collaborative system. Michaud and Vu (2001) have studied human and robot interaction by visual signalling. They have shown that encoded message can be exchanged through coloured flash lights and visual signals can be useful to generate social behaviour between a small mobile robot and a human.

It is also important to consider the benefits of reduced reaction time using an alternative system. A number of studies have been carried out researching the effect of visual signal on reaction time. Murray and Caldwell (1966) reported significantly longer RTs as the number of displays to be monitored increased and number of display figures increased, which supports the Hick's Law where increasing the number of choice will increase the decision time (*Dixon et al, 1996).* There are evidences which show that reaction time to signals can also be delayed as an effect of increases in RT as viewing angle increased (Simon and Wolf, 1963), as well as background noise (Miles et al, 1984) and task difficulty (Warner and Heimstra, 1973). Based on the limitation of viewing angle and position of traditional stack lights, users may have to rely on their peripheral vision to receive the light signal. However, several studies have shown that it usually takes longer for people to notice abnormalities in their peripheral vision (Soichiando and Oda, 2001; Uemura et al, 2012).

5.2 Exploratory study: Robot gesture

5.2.1 Introduction

In collaborative system, human and robots are working in proximity and often one human operator can be managing multiple robots while carrying out other tasks. In this case, an effective robot indication system is valuable in such operation for providing safe and efficient interactions by catching the operator's attention when needed. Manufacturing plants are complex environment with numerous background noises which minimised the effectiveness of audible indication. It has become obvious that the developed system should be a non-contact system which will be visible to the human eye. However, during an interaction the operator should pay attention to the robot most of the time, so the developed system should not distract the operator’s sight away from the robot.

When considering human-robot communication, a number of gesture control systems have been developed in this research for human operators to command robot assistants due to its intuitive characteristic. Thus, it is logical to investigate the possibility for robots to communicate via gestures similar to those used by people in their daily life. Robot gesture communication can allow operator to observe robot status as well as monitoring robot activity simultaneously. Understanding robotic gestures has been a major topic of interest in human-robot interaction (HRI) (Nakagawa et al, 2009). However, there has been little focus on investigating the implications of gesture in industrial human-robots collaboration.

5.2.2 Understanding of robot gestures by the human partner

Industrial robots are available in a broad range of appearance and capability with different features such as number of arms and articulation, degrees of anthropomorphism, size and payload. These features can pose a significant challenge when attempting to incorporate robot gestures for communicating to the human partner during a collaborative task Gesture communication has been investigated with humanoid robots (Riek et al, 2010) but as industrial robots are typically less anthropomorphic interpretation of similar gestures can be a significant challenge. Ende et al (2011) studied gestures in human-human interaction and transferred a selection to a single arm robotic system demonstrating that some are better recognised than others. Gleeson et al (2013) investigated collaborative human gestural communication in assembly task performance for the development of a lexicon for industrial human-robot collaboration and demonstrated that successful cooperation relies on gestures being understood by the human. Although industrial contexts can vary significantly, the aforementioned studies support the idea that human understanding of robotic gestures could be one aspect of successful cooperation in collaborative tasks. Recognising and understanding gestures is likely to determine human operator trust. As Yagoda and Gillan have suggested, Human trust in a robotic teammate "*plays a critical role when operating a robotic system in terms of both acceptance and usage*" (Yagoda and Gillan, 2012). It is a multi-faceted condition determined by the human's mental model of a robot's capabilities and the given task context (Ososky et al, 2013). In a meta-analytic review of factors affecting trust in HRI, it was found that robot performance-related factors (e.g. robot behaviour, predictability etc.) had the highest influence on trust (Sanders et al, 2011). Also, non-predictable robot motions have been found to be hard to understand and subsequently have a negative impact on human well-being (Bortot et al, 2013). Trust has been the topic of many recent studies in the domain of HRI, but little research has been carried out on understanding the influence of industrial robotic gestures on human trust.

Although research has started to place focus on industrial robotic gestural communication, it is still at an infancy level in terms of developing a set of gestures suitable for industrial human-robot collaborative tasks. To warrant seamless human-robot interaction, it is important to investigate the effects of industrial robot gestures on human understanding of the gestures and impact of gestures on users' trust in the robotic teammate.

5.2.3 Effects of industrial gesture motions on users' understanding

A study was designed to test human understanding of robot gestures and the effects of the gestures on their trust in the robot during a collaborative task. This particular study was carried out with another PhD researcher (Charalambous, 2014, p.123) who focused on aspects of human trust. The experiment was published in a conference paper "Effects of industrial robot gesture motions on users' understanding and trust" (Tang et al, 2014).

Sixteen students and staff of Cranfield University (12 male and 4 females, age: *M*=28.6, *SD*=7.1) took part. Five participants were classified as having no prior experience with robots/automation, six participants were classified as having intermediate experience with robots/automation (took part in previous robot experiments) and five participants classified as having high involvement with robots/automation (involved in research projects/used automated machines, such as computer numerically controlled machined).

The robot system used was a Universal Robot UR5 single arm collaborative robot system incorporating a two-finger gripper. Four plastic drain pipes were used approximately 15cm each.

5.2.4 Experiment design

A repeated measures design approach was followed. In the first part participants observed three robot gestures and answered what they think each of the gestures meant. In the second part participants took part in a human-robot collaborative task where the robot utilised identical gestures. The gesture order in the interaction task was randomised to reduce the possibility of order effects.

To identify suitable robotic gestures, previous studies were reviewed (Ende et al, 2011). For this study, three gestures were selected. Gesture selection was based on two criteria: (i) gestures that received high recognition rate without any contextual information provided to participants and (ii) gestures applicable for the needs of the task to be performed in this study. The gestures selected are shown in table 5-2 and figure 5-1.

Table 5-2: Experiments summary table

Robot gesture	Gesture meaning
Robot gesture No1	“Come here”
Robot gesture No2	“Step back”
Robot gesture No3	“Stop”

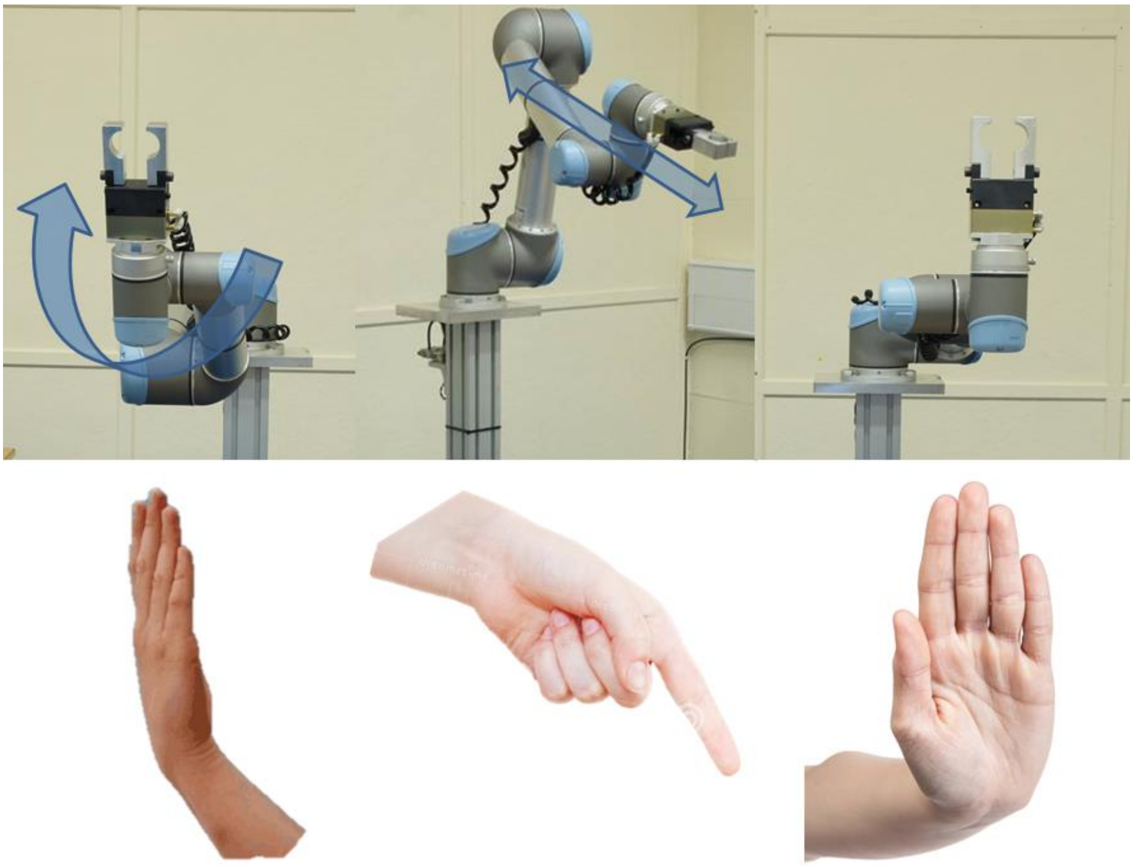


Figure 5-1 - come here, step back (pointing to a floor area), stop gestures

5.2.5 Procedure

This study aims to investigate the effects of industrial robot gestures (independent variable) on: (i) human understanding of the gestures (dependent variable 1) and (ii) impact of gestures on users’ trust in the robotic teammate (dependent variable 2).

Part A: Participants observed three robot gestures, one at a time, in a video format on a computer screen. No task-related information was provided to participants. A text box was provided underneath each of the videos for participants to write what the intended message of each of the gestures was. Each of the gestures was shown on a separate page and participants were allowed to view each gesture three times. Upon completing this, participants were taken to the robot work cell.

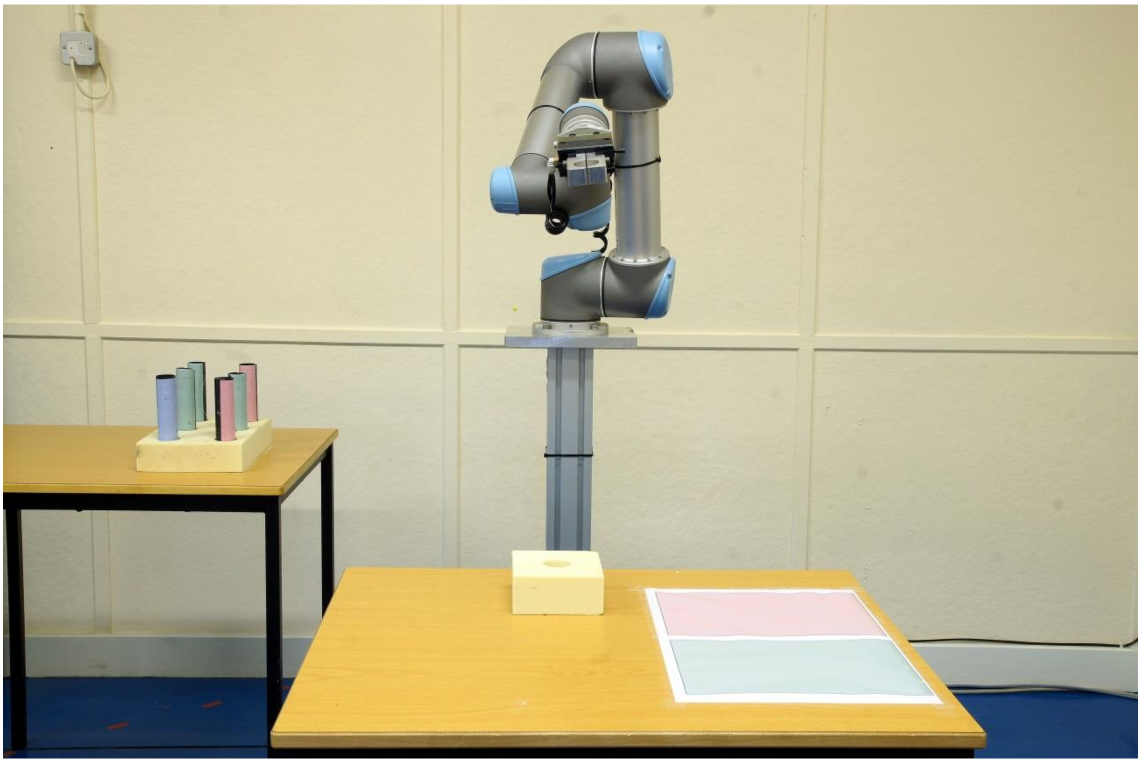


Figure 5-2 - robot gestures experimental cell setup

Part B: Participants took part in a human-robot interaction task. The task involved the robot positioning four small pipes, one at a time, in a pipe holder. Two pipes had a pink sticker, one had a green sticker and one had a blue sticker. A pink and green colour area was created next to the pipe holder as illustrated in figure 5-2. Participants had to select only the pink and green pipes and position them in the appropriate area. When the blue pipe was placed in the holder, the robot utilised the “stop” gesture. When the pink and green pipes were positioned the robot utilised the “come here” gesture followed by the “step back” gesture. At the end of the interaction task, a short semi-structured interview took place. The order of the pipes presented was random to reduce the possibility of order effects. The interview started by asking participants to give their thoughts regarding the interaction and what they think the gestures meant. Then to identify the impact of gestures on users’ trust, participants were asked how the gestures influenced their trust and if they could rely on the robot gestures to complete the task.

5.2.6 Analysis

Written responses from the first part of the study were grouped and interviews from the second part were fully transcribed. A comprehension score for each gesture was obtained from the written responses and the interviews for each participant.

Comprehension score: Participant responses were initially categorised in two categories: correct and incorrect. Correct responses received a weight of 1 and incorrect a weight of 0. To assess whether a response was correct or incorrect researchers generated a correct response for each of the gesture. The correct meaning for each gesture is shown in table 5-1. Any positive answer not considered 100 per cent correct was subjected to a different algorithm to evaluate the comprehension score. The algorithm was based on a study conducted by (Corbett et al, 2008) and includes three more categories: likely, arguable and suspect, each of which carries a different weight. Once the responses were tabulated, the comprehension score was calculated as shown in table 5-3. Total comprehension score was obtained by summing the individual scores of each category.

Table 5-3: Complete categorisation for comprehension score

Correctness	Weight	Frequency	Comprehension Score
Correct	1	A	[(A*Weight)/Total answers]*100
Likely	0.75	B	[(B*Weight)/Total answers]*100
Arguable	0.5	C	[(C*Weight)/Total answers]*100
Suspect	0.25	D	[(D*Weight)/Total answers]*100
Incorrect	0	E	[(E*Weight)/Total answers]*100

Impact of gestures on trust: Transcripts were analysed by coding volume of text frequently discussed among participants into common themes. This approach led to the development of a coding template. The template structure was revised iteratively to ensure it reflected the data in the most suitable manner.

Inter-rater reliability: Analysis of inter-rater reliability was carried out to confirm the level of consensus between raters and, therefore, the suitability of the measures used to measure gesture understanding and trust.

For the comprehension scores, one of the two researchers categorised the responses for parts A and B of this study and obtained a comprehension score. A second researcher categorised the responses individually. Results were then tabulated for calculation of the Cohen's kappa statistic, for this data, chosen because it shows the level of concordance between ratings corrected for the probability of agreement by chance thus giving a more conservative result when compared to simple agreement percentage. The Cohen's kappa for part A was 0.72 and for part B was 0.63 indicating there was 'substantial agreement' among raters (Landis and Koch, 1977).

The coding template developed as described above was used by an independent rater to code the interview transcripts. Results were then tabulated for calculation of the Cohen's kappa statistic. The Cohen's kappa was 0.616 suggesting 'substantial agreement' among raters (Landis and Koch 1977).

5.2.7 Results

The aim of the user study was to investigate human understanding of robotic gesture and their impact on users' trust in the robot. Results indicated that comprehension scores were lower in part A when compared to part B (Table 5-4).

Table 5-4: Comprehension score table

Experiment part	Gesture 1 (Come here)	Gesture 2 (Step back)	Gesture 3 (Stop)
Part A	51.6%	4.7%	3.1%
Part B	87.5%	29.7%	43.8%

With the exception of gesture 1, gestures 2 and 3 received very low comprehension scores for part A (4.7% and 3.1%). For part B on the other hand, all gestures received higher comprehension scores (87.5%, 29.7% and 43.8%).

5.2.8 Impact of robot gestures on users' trust

Impact of robotic gestures on user's trust pointed four major themes (table 5-5).

Table 5-5: Major trust related themes

Trust related theme	Frequency
Gesture understanding and intuitiveness	14
Robot gestures motion	12
Experience and familiarisation development	5
Robot programmer	5

The majority of participants felt that the impact of robot gestures on their trust was mainly influenced by two factors: (i) gesture understanding and intuitiveness and (ii) human-likeness of the robot gestures. Another common aspect influencing trust in the robot was the development of familiarisation with the gestures and the robot. Some participants reported that their trust in the robotic assistant was due to trusting the person who developed the program rather than the gestures.

5.2.9 Evaluation

In part A, with the exception of the "come here" gesture (51.7%), the "step back" and "stop" gestures received very low comprehension scores (4.7% and 3.1%). This is congruent with a previous study (Ende *et al,* 2011) where the "stop" and "step back" gestures received a much higher identification rate (92% and 84%

respectively). A possible explanation for the low comprehension score in our study is that no context information was provided in the videos. This appears to have had some influence since all gestures received a higher score (87.5% gesture 1, 29.7% gesture 2 and 43.8% gesture 3) in part B. However, for part B gesture 2 ("step back") still appears to receive a low comprehension score (29.7%) when compared to gesture 1 ("Come here") and gesture 3 ("Stop") (87.5% and 43.8%). This indicates the lack of gesture 2 to convey the appropriate message.

In relation to the impact of robotic gestures on users' trust, it was found that if they could not understand the gestures their trust decreased. In addition, participants found trust in the robot increasing with human-like gestures. These two themes appear to be interrelated. It was discussed that human-like gestures are more easily understood and are considered more trustworthy. To this end, most participants found gestures 1 ("Come here") and 3 ("Stop") human-like and some participants described them as "universal gestures" in human-human non-verbal communication. Gesture 2 on the other hand, was the hardest to interpret and this had a negative impact on their trust. This is reflected in the comprehension scores obtained for part B and can potentially explain why gesture 2 received the lowest comprehensive score. This appears to be consistent with the notion that human-like motion enhances social acceptance and comprehensibility of the gestures (Gielniak et al, 2013).

Also, some participants suggested that developing familiarisation with the gestures was important in order to trust the robot. Initially participants felt unsure approaching the robot, particularly when the "Come here" gesture was initiated. This was because they could not predict what the robot would do. However, after familiarising themselves with the gestures, participants reported having higher trust in the robot that enabled them to overcome the initial surprise effect. This is consistent with the notion that experience and familiarisation with robotic teammates foster trust in human-robot interaction (Ososky *et al,* 2013).

Some participants reported that their trust in the robot was due to trusting the person who installed program rather than the gestures. Interestingly, these participants were classified as having high exposure to robots. These participants achieved a lower comprehension score when compared to participants with intermediate or low experience. It appears that participants with higher exposure to robots appear to already have formed certain expectations towards robots.

5.2.10 Conclusion

In this study we investigated the implications of three gesture motions performed by a small industrial robot on: (i) human understanding of the gestures and (ii) user's trust in the robotic teammate.

An important result is that human-like robot gestures, such as "come here" and "stop" were found intuitive and can convey the intended message more accurately. The "step back" gesture on the other hand was not well understood which was reflected in the comprehension scores in both parts of the study. Thus, when considering robot gestures for industrial applications, more research is required to identify a selection of gestures that can be applied across a variety of robots. The investigation on the impact of robot gestures on users' trust identified that being able to correctly comprehend the intended message of robot gesture has a positive impact on trust. Subsequently, human-like robot gestures appear to foster trust in the robot when humans are collaborating with a robot to complete a task. Also, it was found that experience and familiarisation with robotic gestures can foster trust in the robotic assistant. At the same time, participants with higher exposure to robots were found to place more trust in the robot programmer rather than the robotic gestures.

The study has shown that robot gesture communication requires additional research to identify a set of gestures that can be applied across a variety of robots. Therefore, some gestures which are not easily interpreted can potentially be improved when coupled with other indication method such as lamp signal or audio notification.

5.3 The development of an advanced robot indication system

5.3.1 Introduction

In collaborative system, human and robots are working in proximity and often one human operator can be managing multiple robots while carrying out other tasks. In this case, an effective robot indication system is valuable in such operations, providing safe and efficient interactions by catching the operator's attention when needed. Tower lights are commonly used in production cells as a means of indicating a machines' status, but these devices were not designed for industrial collaboration robots so their effectiveness can be significantly reduced. For example, the positioning of tower light is restricted in a way that should not hinder the movement of the robot. On the other hand, the distanced light signals can divert operators' attention away from the robot and their task. The exploratory study described in chapter5.2 shows that industrial robot generated gestures can be difficult to comprehend without the assistance of other communication methods. Thus, an alternative indication system is required. This chapter describes the development of an intuitive and effective robot indication system. The aim of this research is to develop a signalling device for industrial collaborative robot which can attract the operator's attention under multi-tasking situations as well as communicate the robot's status to the user effectively.

5.3.2 Indication system for industrial automation

The industrial stack light is based on a system that is used and seen in everyday life: the traffic light system. The traffic light system is considered to be intuitive because the concept of the three colours red, yellow and green is taught to most people at a young age. The intention is to enable users to perceive the robot's state without the requirement for significant cognitive workload which will speed up the users' response time to the signal as well as reserving metal capacity to focus on other tasks.

Apart from traffic signals, the traffic light system is also used in other everyday life situations. For example the Food Standards Agency has implemented the

Traffic light system in food package labelling (Food Standards Agency, 2007). A number of studies investigated the effect of the “Traffic Light” labelling system, where red, yellow and green represent high, medium and low respectively in nutritional content of the food. Research evidence suggests the time required to comprehend the labelling has decreased, and some have stated a significant decrease in time required to obtain information from the labels (Malcolm et al, 2008). It is also reported that it has a positive effect on the decision making of consumers (Kelly et al, 2009; Sacks et al, 2009; Feunekes et al, 2008). Research by the Food Standards Agency has shown that consumers prefer traffic light labelling because it offers key information "at a glance" (Wise, 2013).

The traffic light system has also been the choice of signalling system for time critical application such as Formula one racing. Team Ferrari has been using a traffic-light system for signalling to the race driver during pit-stop to indicate that it is safe to proceed back to the race track, the strategy was terminated after a manual error in 2008, but it was tested again by Team Mercedes two years later with the intention to reduce time for pit stops (motorsport.com, 2010; BBC Sport, 2008). Research evidences indicate the “traffic light” colouring system is an effective way to communication information to users. Thus, the developed system uses the red, yellow and green colouring system to indicate different machine status.

5.3.3 Design concept

The idea of the design concept is a visual indication system which constantly communicates the robot status to human operator, and the operator should notice a change in robot status at a glance. As illustrated in figure 5-3, the indication system uses different colours to indicate the robot’s state in different operating modes. The collaborative robot system can be operating in fully automatic mode to carry out repetitive tasks at maximum speed, or collaborative mode which requires some human input. For instance, the robot may encounter uncertainties during the automatic mode due to variability. In this case, the robot changes from a green to a red signal to alert the operator. In a different scenario the robot operation requires cooperation with an operator, the robot can notify the operator by a flashing blue signal and acknowledge with a solid blue signal once an operator becomes engaged in the task.

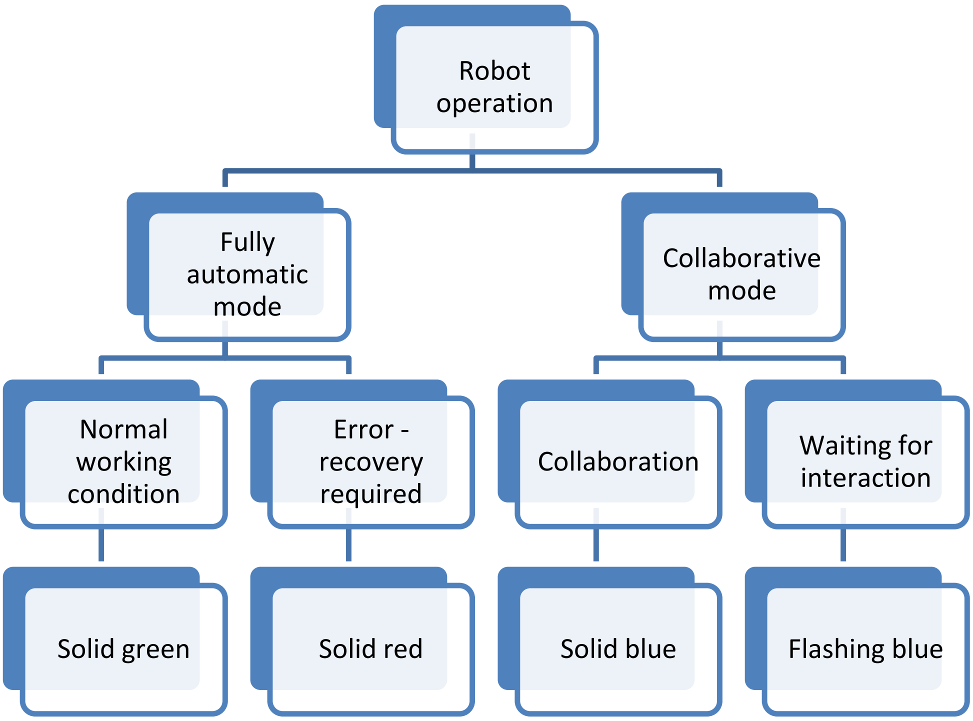


Figure 5-3 - indication system operating diagram for collaboration in proximity

For many industrial settings, a larger industrial robot will be used instead of a safety rated collaborative robot similar to the one used in this research. These industrial robots require safety monitoring of the robot working envelop, and the human must be separated from the movement by a safety distance. In this case, the signal architecture can vary slightly to the one designed for collaboration in proximity. For example, red, yellow and green can be used to display the proximity of the operator to the robot in terms of danger zone, warning zone and safe zone respectively (as illustrated in figure 5-4). A flashing blue signal is still applicable as a notification for a collaboration request and solid blue for confirmation of interaction.

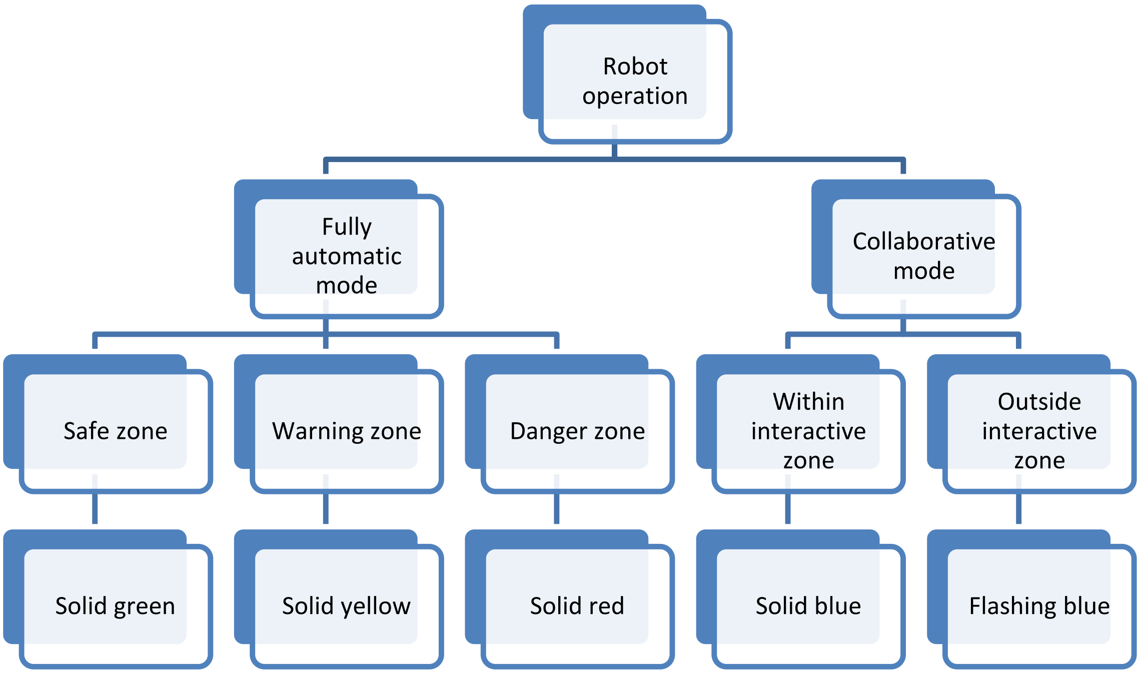


Figure 5-4 - indication system application suggestion for larger industrial collaborative robot

It is known that the users have to pay attention to the robot in operation so ideally the robot should be the source of the signal. The idea is to integrate an external light indication system onto the robot arm, thus, the robot becomes the indication light source. As illustrated in figure 5-5, the robot can be equipped with a layer of glowing light skin which emits appropriate light signals.

Figure 5-5 - the glowing robot concept

A glowing robot light skin is achievable using organic light-emitting diode (OLED) technology. OLED light sheet is available on the current market in variety of size and intensity (figure 5-6). These light sheets are flexible and fully programmable when controlled with suitable controller. Their latency is lower than other display technologies such as liquid crystal display (LCD) (Rejhon, 2013). Thus, OLED light sheet can be used to develop device which cover the exterior of an industrial robot to display robot signals with fast response.

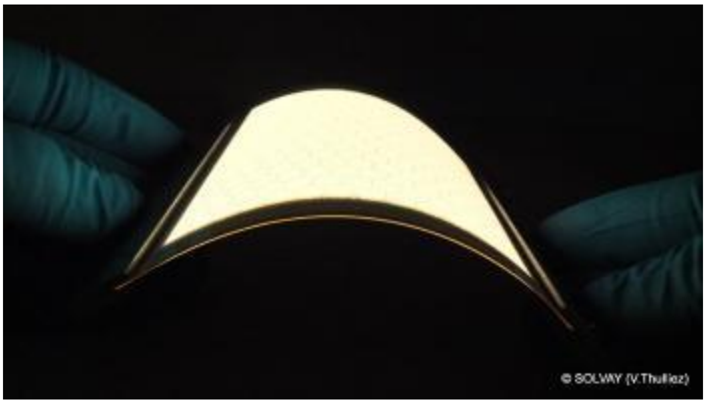


Figure 5-6 - OLED light sheet, image courtesy: http://www.oled-info.com/epigem-develop-flexible-anode-film-flex-o-fab-project

However, the cost of OLED light sheet is relatively high when compare with other viable lighting technologies such as fully programmable LED light strips. The cost of this technology should eventually decrease from the current level which enables it to be a feasible low cost solution. Nevertheless, the current cost is still insignificant relative to the cost of an industrial robot. For the development in this research, flexible LED light strip is used as a substitution due to its low cost and availability.

5.3.4 Experiment for concept validation

An exploratory experiment was carried out to compare the effectiveness of a tower light and the design concept in terms of participant's reaction time, awareness and acceptance. The purpose of the experiment is to investigate more effective ways of visual signalling in industrial human-robot collaborative. There are currently a number of visual signal technologies being used in industrial robot systems, but each has their limitations. This experiment will be setup to measure the effectiveness of current technologies and explore their limitations when compares to the proposed concept. Each method will be tested in isolation and their effectiveness will be measured by the participants' points of interests and reaction time using an Eye Tracker device and a timing system. The Eye Tracker will be used to take videos of the participants' view during the experiment *(Santner et al, 2013)*. The results of this experiment are used to make suggestions for system refinement and future development.

5.3.5 Standards on indication system for industrial machinery

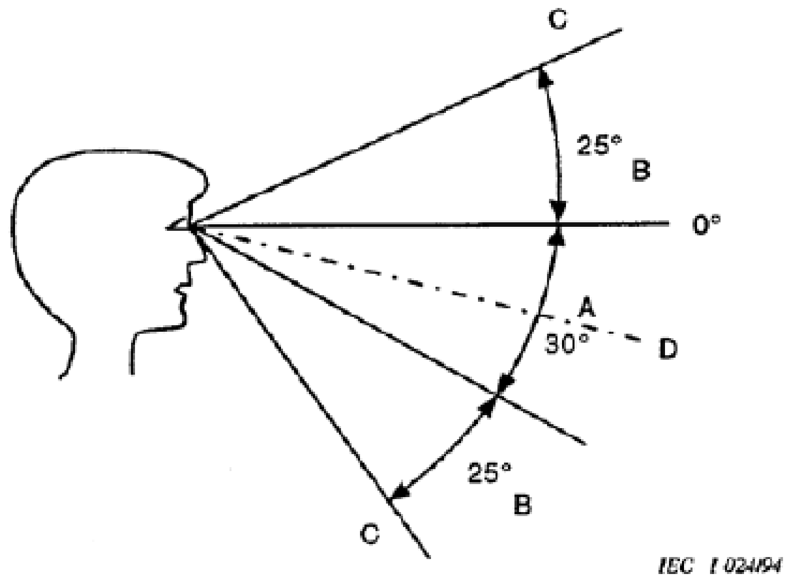
The experiment setup must represent a typical industrial setting. Thus, it is important for both indication light systems to position according to standards. The setup requirements of indication system for industrial machinery are described in *EN 60073:2002* and *EN 61310-1:2008*. *EN 60073:2002* highlighted the importance to assign specific meanings to specific colours and to ensure that colours are easily identifiable and distinguishable from the background colour and any other assigned colours (table 5-6).

Table 5-6 - Meaning of colours - General principles EN 60073:2002

Colour	Meaning		
	Safety of persons of environment	Condition of process	Sate of equipment
Red	Danger	Emergency	Faulty
Yellow	Warning	Abnormal	Abnormal
Green	Safe	Normal	Normal
Blue	Mandatory significance		
White Grey Black	No specific meaning assigned		

EN 61310-1:2008 suggests that a human-machine interface needs to convey safety-related meaning for the safe use and monitoring of machinery for exposed persons and operators, and specific signal codes should be used to decrease the mental work-load of an operator and exposed persons. Active signals such as tower lights should be provided to signal a hazard and to alert operators to take a specific course of action.

The standard specifies that the position of light source in the vertical field of vision should not exceed 25 degrees above horizontal eye level or less than 55 degrees below eye level as illustrated in figure 5-7. Recommended zone is between zero degrees to 30 degrees below eye level. Natural line of sight is around 15 degree below eye level.



Zone A: recommended
Zone B: acceptable
Zone C: not suitable
Zone D: natural (median) line of sight

Figure 5-7 - zones of vertical field of vision

Position of the light source in the horizontal field of vision should be within 50 degrees of the natural line of sight or centre line from horizontal vision for both left and right side of view. The recommended zone is within 25 degrees from the centre line for both sides as shown in figure 5-6.

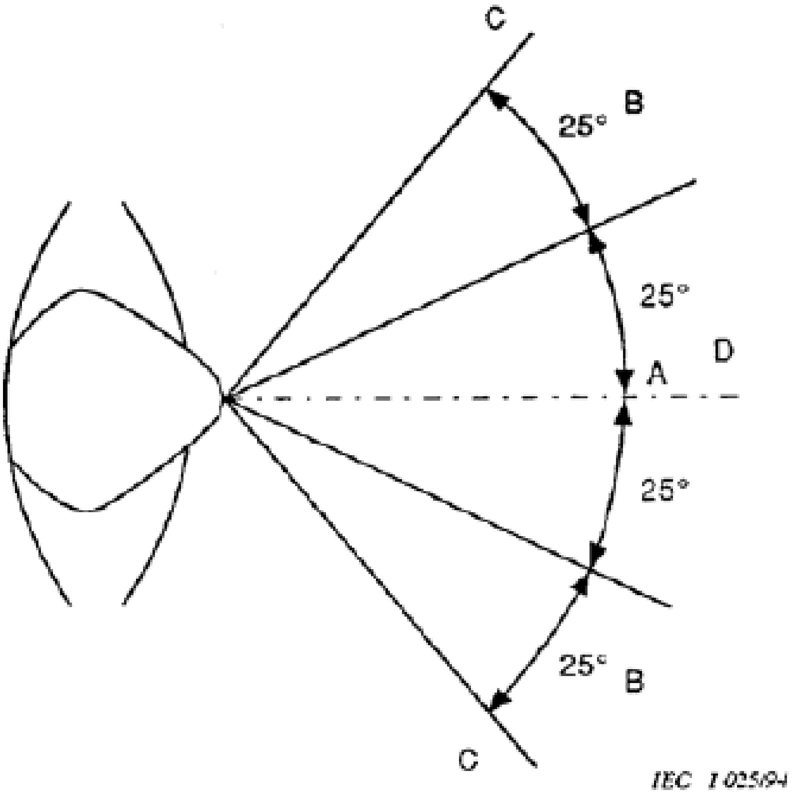


Figure 5-8 - zones of horizontal field of vision

5.3.6 System comparison: integrated robot light versus tower light

This study aims to ascertain whether the ability of an operator to monitor and effectively react to changes in the robot system state can be improved by the developed robot indicating concept. Operators will be asked to carry out an assembly task while monitoring and reacting to red and green lights on both the moving robot and a standard light tower.

The experiment aims to ascertain whether the robot indicator design concept compared to an industrial tower light increases awareness, reduces workload and improves reaction times for the operator. The objectives are to evaluate the performance of participants completing an assembly task in two different orientations to the robot (forward and side on), measure the reaction times of the participants to red and green lights on the robot body and a light tower while the robot completes a pick and place task, and to measure the visual fixations and saccades of participants throughout the task which supports the improvement phase of the design.

5.3.7 Method

Sixteen people from the general population of Cranfield University participated in the experiment. 12 of them were males and four of them were female, and all participants were right-handed. Their age ranged from 23 to 56 years with mean of 30 (SD = 9.88). Each experiment took around 35 minutes. This experiment utilised a counterbalanced repeated measures approach with random sampling to assess the effectiveness of two different types of warning system; tower light, and integrated robot light.

The experiment took place in a 3960mm x 3900mm laboratory area surrounded by 4 sides of wall. The robot arm was positioned on top of a stand at a height of 1030mm. The robot has 850mm reach with a circular working envelop. A 1220mm x 800mm robot worktop with a height of 920mm was positioned next to the robot base with a 200mm clearance. A manual workbench with surface area of 630mm x 785mm was attached to the robot worktop at the same height. Both worktops had a matt surface which minimised reflection of the indication lights. Each participant had to operate in both a forward and side position in respect to the robot worktop orientation. The industrial tower light was positioned at a height of 1210mm in a location that was visible to participants in both test positions without any obstruction from robot movements as shown in figure5-10. Both the tower light and integrated robot light were within 10degrees of the horizontal line of sight which is recommended by the standard. The robot indication light was wrapped around the robot which covers the area between the elbow and the wrist, the wrist and the base. A floor plan of the experimental area is illustrated in figure 5-9.

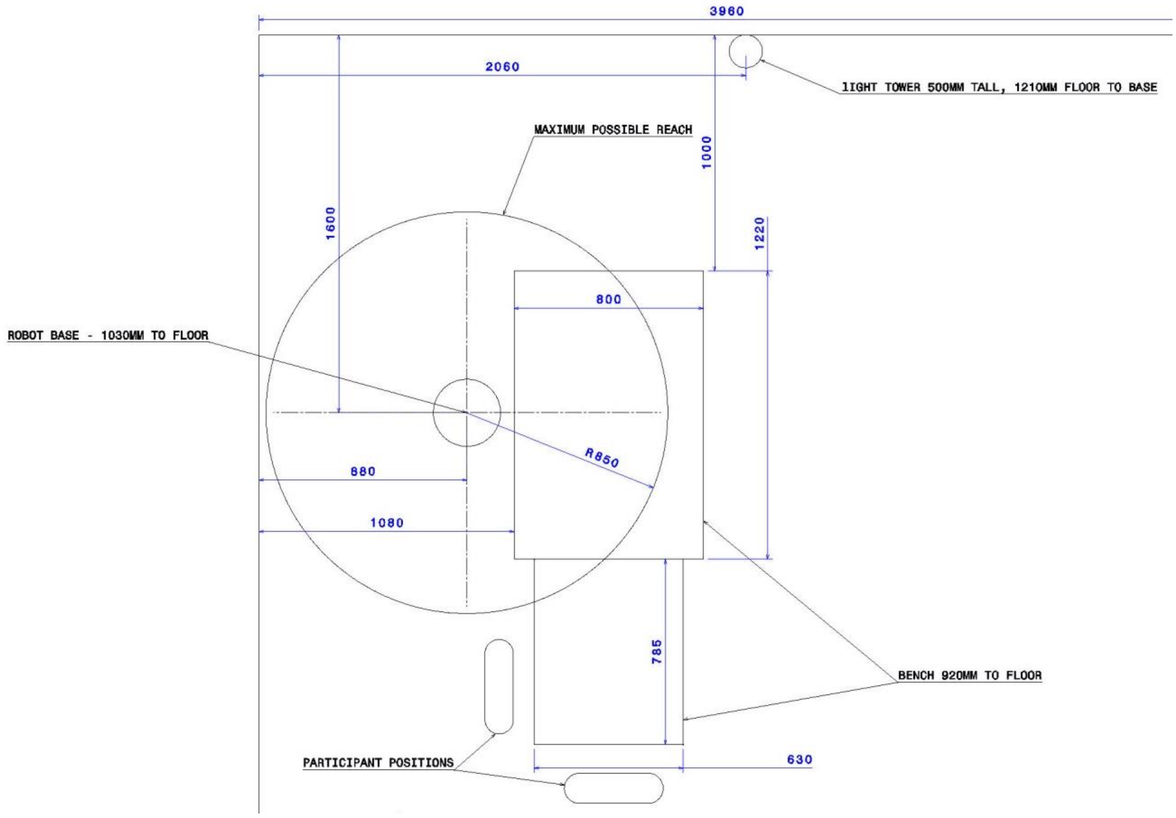


Figure 5-9 - Experiment area layout

The experiment area had no direct sun light and the lighting level was kept constant at 400lux throughout the entire experiment. For simplicity, only the green and red lights were used on both indicating devices. Both green and red lights of the tower light emit 1300lux of lights while the LED light strip of the concept design emits 600lux in green and 230lux in red due to the limitation of the lighting system (figure 5-10).

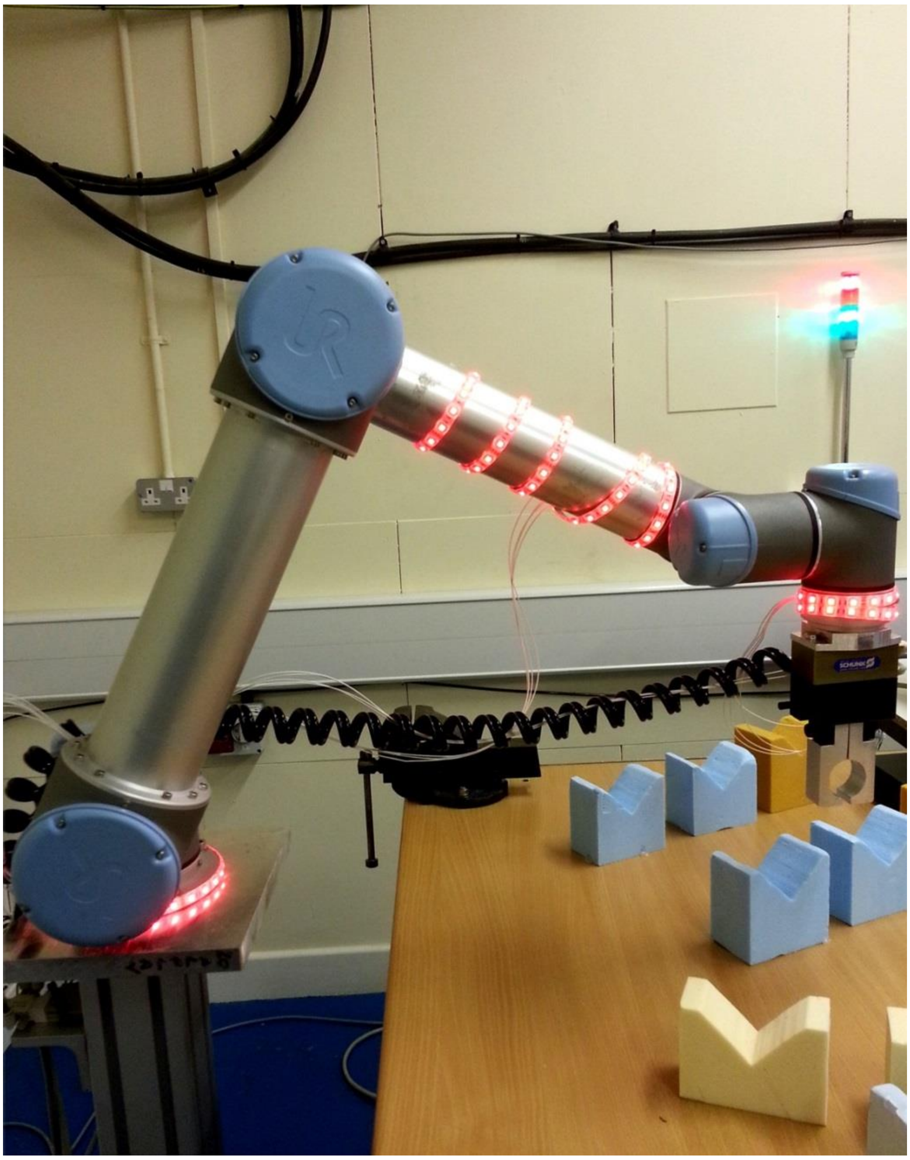


Figure 5-10 - viewing angle from the side position, both types of light were lit for illustration

The participants' eye moments were recorded using a mobile head-mounted eye-tracker (SensoMotoric's BeGaze© eye tracking system). The device is portable which enables participants to wear and allows them to move their head naturally without limitation during the task. It is shaped similarly to safety glasses which simulate the physical restrictions in real working condition when safety wears are worn. The reasons for using this equipment are to ascertain common points of interest in different scenarios, and the effect of using the developed signalling method. Thus, the hypothesis can be verified and the data can also support other findings. This eye tracking equipment consists of glasses with in-built cameras that track human eye pupil activity while simultaneously recording field of vision. All participants wore the equipment throughout the experiment. The tracking data was analysed using Begaze software utilising Area of Interest (AOI) semantic gaze mapping. The AOIs mapped include the manual task work top, robot work top, robot (with and without light on), and the tower light (on and off). An illustration of the experiment condition is shown in figure 5-11.

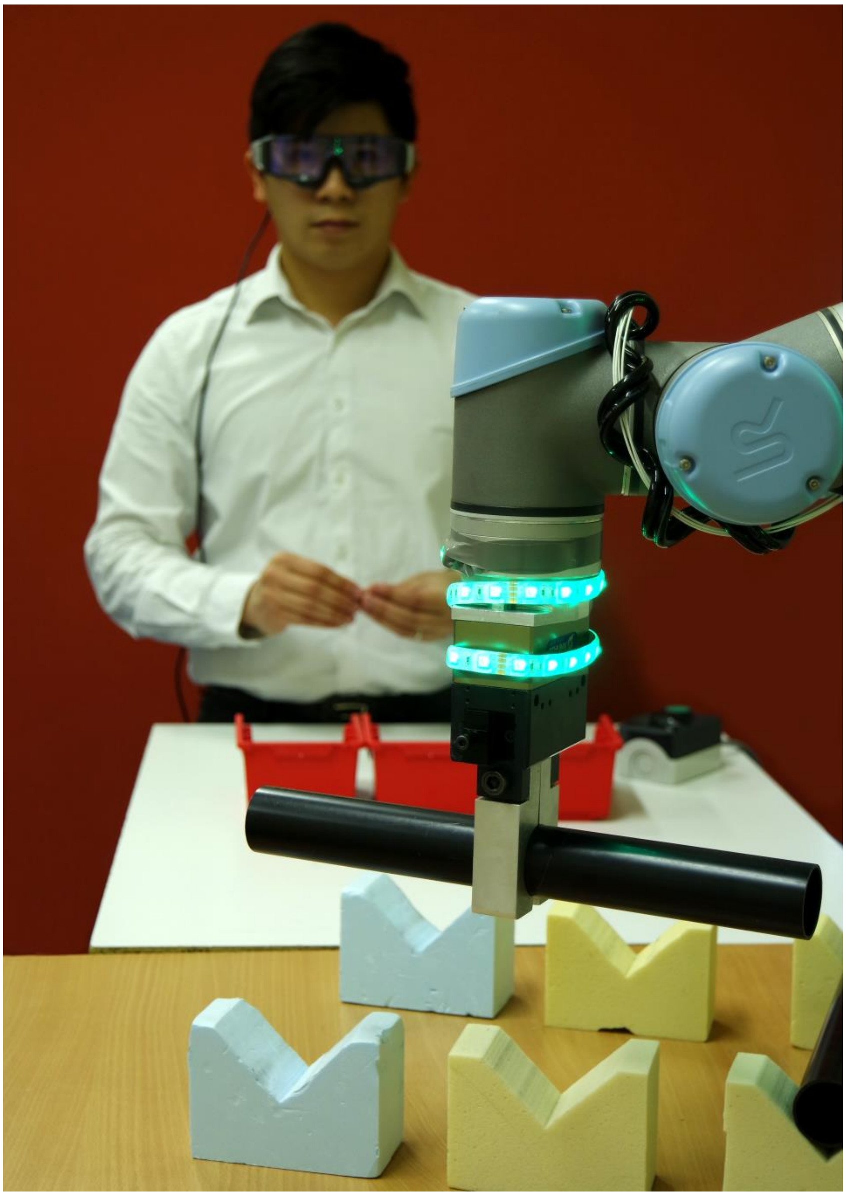


Figure 5-11 - illustration of the robot indication systems comparison

Participants completed an assembly (nut, bolt and washer) task, while a robot completed a simple pick and place task nearby. The participant was asked to react by pressing a button when they saw a green or a red light on the robot or the tower light. They completed the task four times in two different positions (straight on and side on) while being video recorded. The "Time to complete" was benchmarked with each participant by measuring the time taken to perform five sets of assembly prior to the test. The performance index is calculated from test result using (1).

$$\rho = \frac{T}{b_n} \tag{1}$$

T is the time to complete a single assembly during the experiment sequence, and b_n is the benchmark time to complete a single assembly.

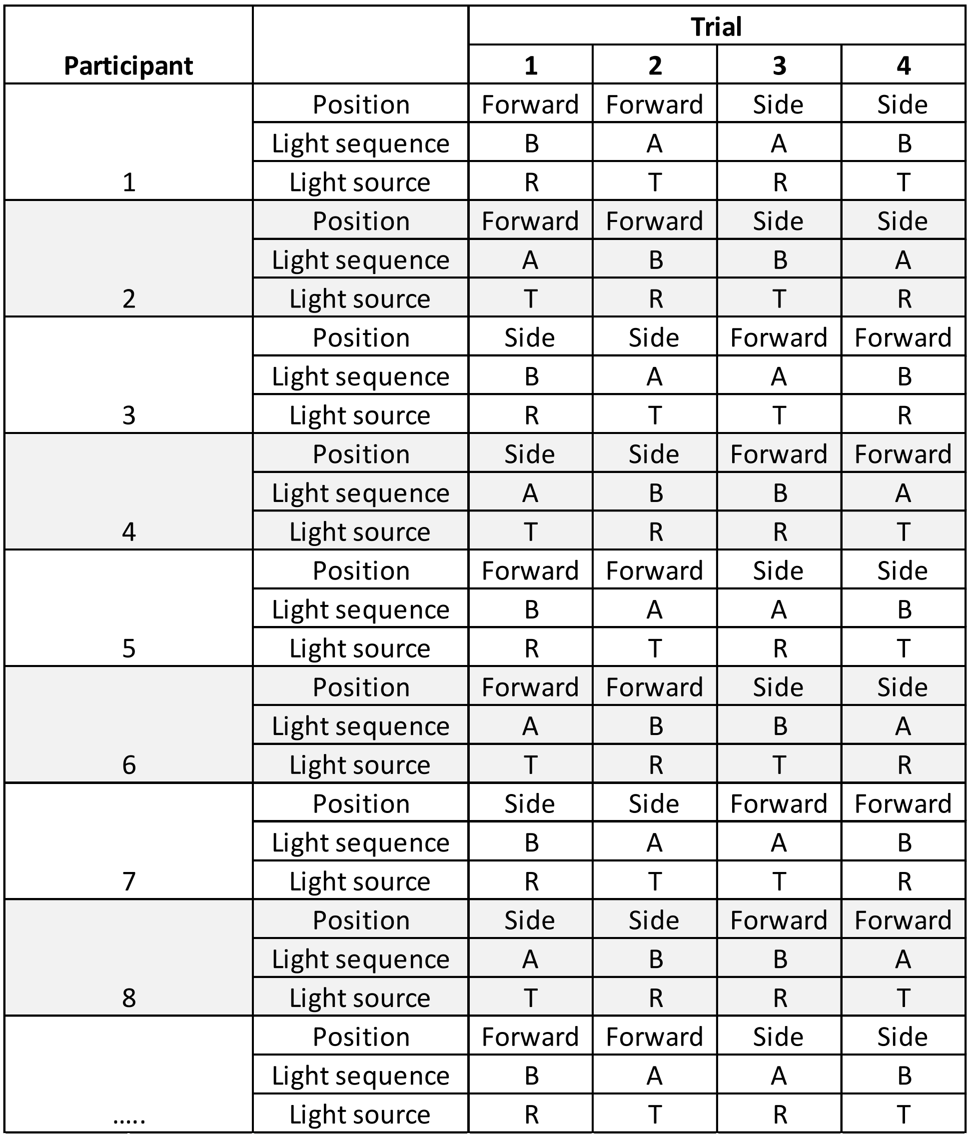
The experiment segments must be carried out enough times to collect an adequate amount of data as well as for counter-balancing results. However, due to the repetitive nature of the task it was important to restrict the length of the experiment and number of segment to minimise tediousness. As Walers et al (2011) have demonstrated, a long-term Human–Robot Proxemics study with repetitive experimental procedures can cause boredom which ultimately lead to early exit of participants. This highlights restrictions of keeping experimental controller conditions, and the necessity of planning realistic, engaging and varied experimental scenarios. Four pilot studies were carried out prior to the actual test to make refinements to the experimental process. No major changes have been made apart from the wording of questionnaires.

A semi-structured interview was carried out to gather subjective responses to the stimulus after each 3-minute segment. A final questionnaire was also used to gauge relevant effects of different settings. Their task performance, visual fixations, and their reaction times to the light signals were measured using different means. These were compared against other data and were treated in order to minimise order effect.

The experimental procedures are detailed sequentially as follows:

1. Participants had the trial explained to them and were asked to sign a consent form. They were told what they would be expected to do, and also given key information:
    a. That they can leave at any time
    b. That the trial will be recorded (via video and eye tracking glasses)
    c. About data protection and anonymity
2. Participants were asked to fill out a questionnaire including questions on:
    a. Physical attributes (age, height, vision)
    b. Technology experience and attitudes
    c. Work experience
    d. Assembly / physical work experience
    e. Alertness (subjective)
3. Participants were shown the work area and told what the robot would do.
4. They had the assembly task explained to them and allowed to have a try.
5. They were asked to complete 5 sets of assemblies as fast as they could, four times. These were timed and used for matching purposes during analysis. This was used to minimise learning effects during the trial.
6. Participants were fitted with the eye tracking glasses and they were calibrated.
7. The trial began and the participants completed 4 trials lasting 3 minutes each where they were told to complete as many assemblies as possible. The light sequence was pre-programmed and showed 10 green lights and 10 red lights (lights stayed lit for 3 seconds). There were 2 different light sources and 1 light source was used in each sequence at a time. There were 2 different light sequences and participants were randomly assigned to positions, light sources and light sequences to minimise order effects as illustrated in figure 5-12.
8. Participants completed two trials facing the robot, and two trials to the side of the robot with a 90 second break in between each. At the end of each trial they were asked if they thought there was an equal amount of lights displayed for the robot and the light tower, as well as the ease of

spotting the light, observation of robot movement and tiredness of performing the task. The robot movements were the same for each trial and participants were expected to press a button as soon as possible when an indication light lit up.



Participant		**Trial**			
		1	**2**	**3**	**4**
1	Position	Forward	Forward	Side	Side
	Light sequence	B	A	A	B
	Light source	R	T	R	T
2	Position	Forward	Forward	Side	Side
	Light sequence	A	B	B	A
	Light source	T	R	T	R
3	Position	Side	Side	Forward	Forward
	Light sequence	B	A	A	B
	Light source	R	T	T	R
4	Position	Side	Side	Forward	Forward
	Light sequence	A	B	B	A
	Light source	T	R	R	T
5	Position	Forward	Forward	Side	Side
	Light sequence	B	A	A	B
	Light source	R	T	R	T
6	Position	Forward	Forward	Side	Side
	Light sequence	A	B	B	A
	Light source	T	R	T	R
7	Position	Side	Side	Forward	Forward
	Light sequence	B	A	A	B
	Light source	R	T	T	R
8	Position	Side	Side	Forward	Forward
	Light sequence	A	B	B	A
	Light source	T	R	R	T
…..	Position	Forward	Forward	Side	Side
	Light sequence	B	A	A	B
	Light source	R	T	R	T

Figure 5-12 - experiment sequences; R=Lights on robot, T=Tower light

9. Participants were removed from the area, the glasses removed, and asked to complete a questionnaire with questions relating to:
    a. Awareness

   b. Difficulty of task
   c. Preference on indication light system
   d. Experience of wearing the eye tracker
10. Participants were asked general questions relating to the task and the visibility of the tower and the robot. Participants were then debriefed.

5.3.8 Evaluation

The participants were asked to react to different signal lights by pressing a button in front of them. The button was connected to a National Instrument logging system which recorded participants' reaction time.

The results show that it takes longer for participants to react to light signals from the tower light source as illustrated in figure 5-13. The difference is subtle but overall it always takes longer for people to react to the tower light source than the integrated robot light.

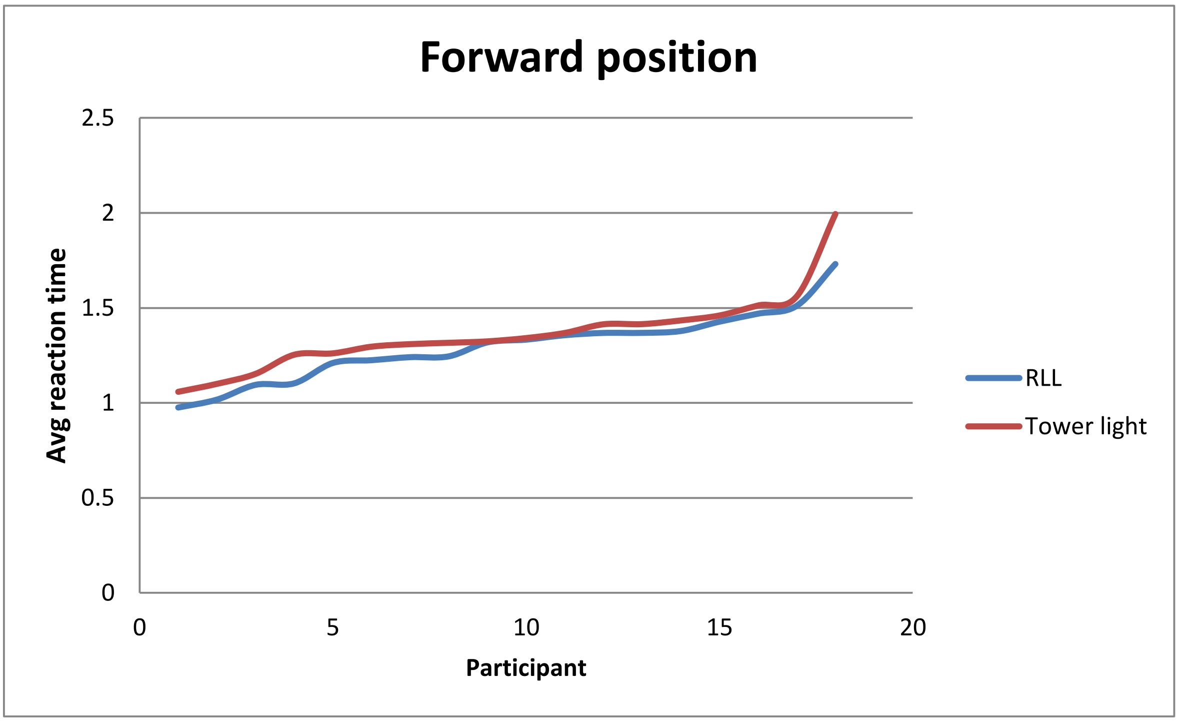


Figure 5-13 - reaction time in forward position

Similarly in side position, participants generally have longer delays before reacting to the tower light than the integrated robot light. The difference is greater in the side position than the forward position as shown in figure 5-14.

Figure 5-14 - reaction time in side position

Each signal light was on for three seconds and the participants were permitted to react to the signal by pressing the button, if participants fail to react within three seconds it will count as a miss even if the button is pressed. The difference in number of misses between the two light sources is significant as shown in figure 5-15. The integrated robot light has received a total number of five misses in both the forward position and side position, whereas the tower light has 21 misses in forward position and 32 misses in side position.

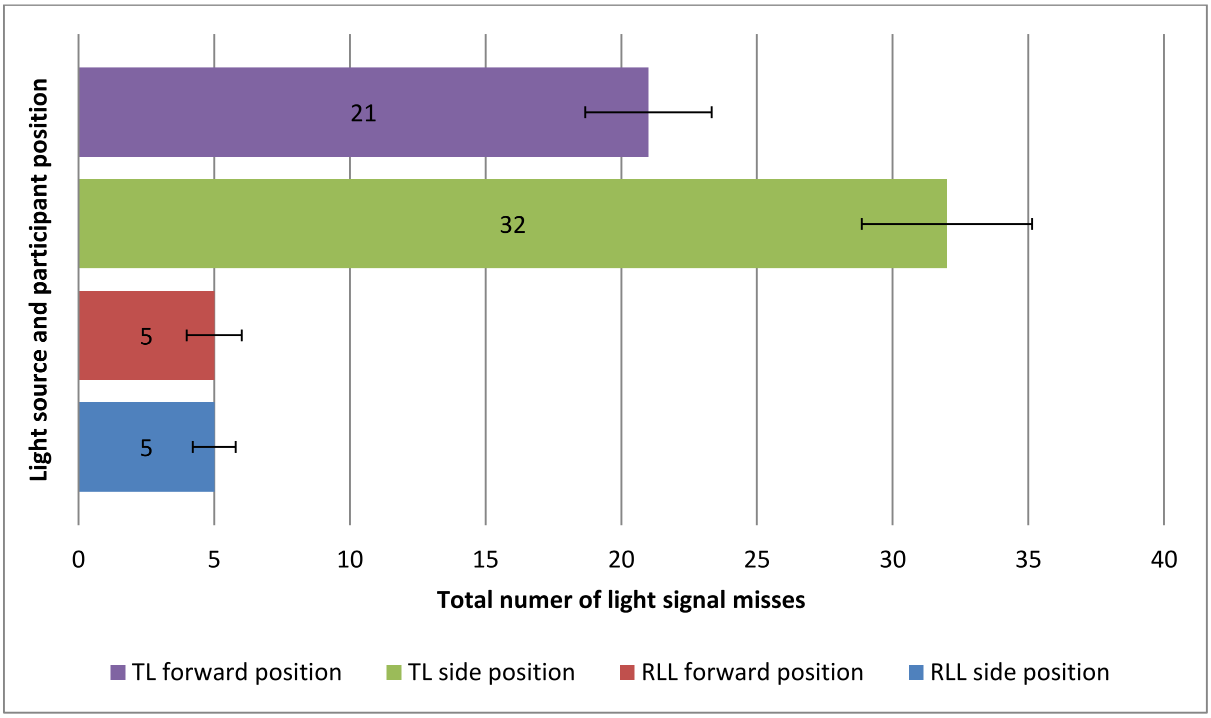


Figure 5-15 - total number of missed light signals of all scenarios

The task performance is measured by comparing the completed assembly count at the end of each experiment segment to a benchmark as explained in the method chapter. Photographic evidence were taken after each segment of the experiment for counting purposes, figure 5-16 shows an example of a photo after an experiment segment. A performance index is calculated for each segment using formula (15). No direct correlation has been found between task performance versus reaction time, and task performance versus number of misses. As shown in figure 5-17, the overall task performance levels are similar across different scenarios where the integrated robot in side position has received the highest score.

Figure 5-16 - photographic evidence of task performance

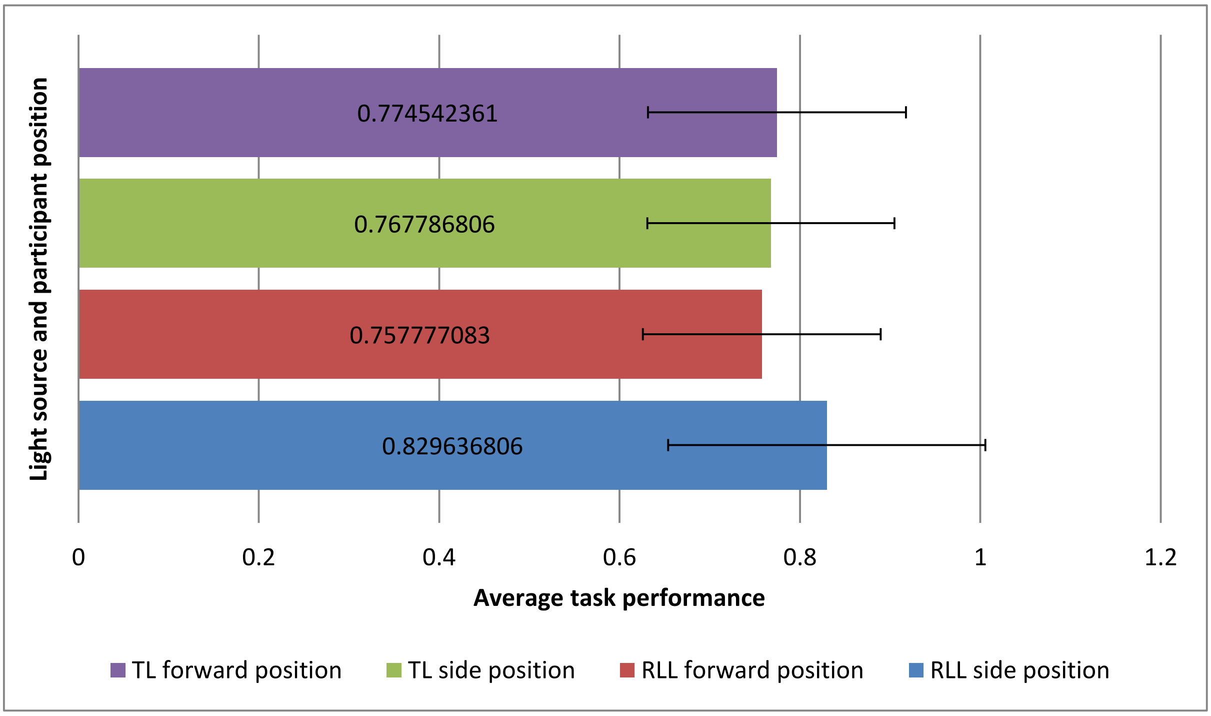


Figure 5-17 - average task performance in all scenarios

After each experiment segment a semi-structured interview was carried out to record the experience of participants. One of the questions was to score the ease of monitoring the signal light. A 7-point scoring system was used, where 7 is the easiest and 1 is the most difficult. Participants found it easier to monitor signal lights in the forward position than when standing in the side position. The integrated robot light received a higher score in both cases as shown in figure 5-18.

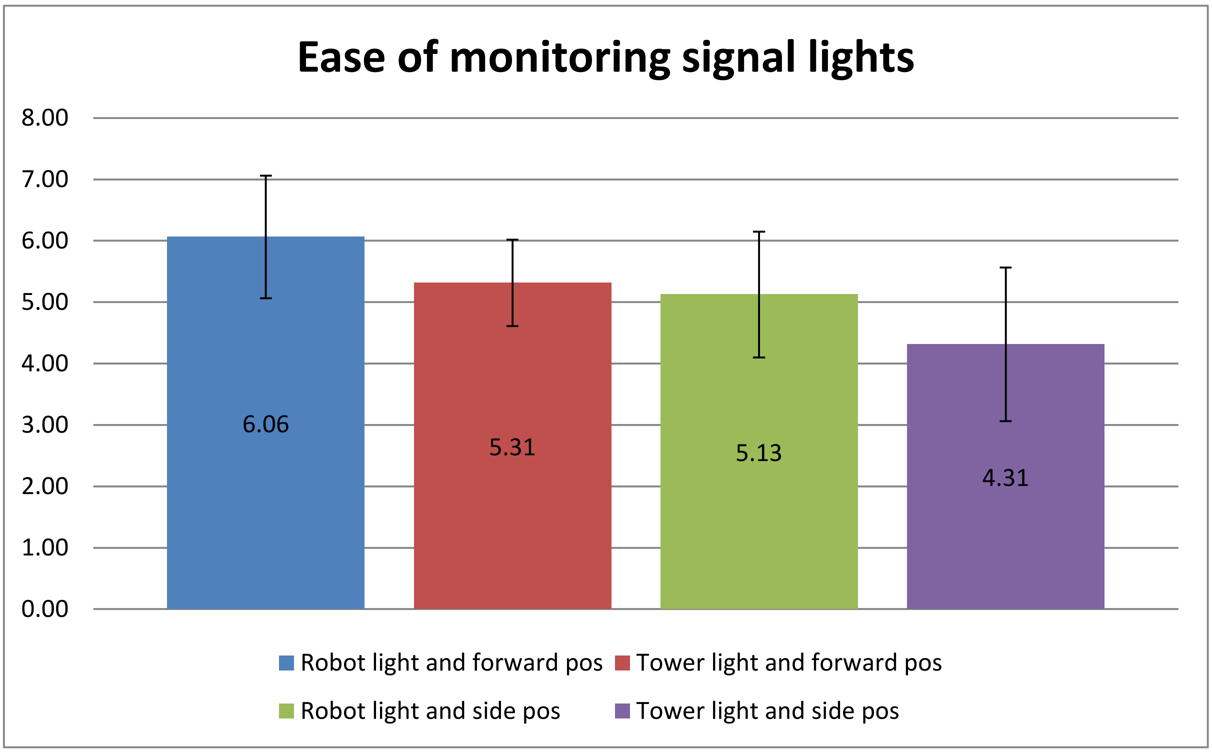


Figure 5-18 - average ease of monitoring light signals of all scenarios

Participants wore a pair of eye tracking device throughout the experiment to track their eye movement in different scenarios. Heat maps were constructed to illustrate the average fixation time in various AOIs (figure 5-19 and 5-20). It is shown that in scenarios where participants have to observe signal from the tower light source a lot of time is spent looking at the tower light which reduce time spent looking at the manual work top where the assembly task is being carried out.

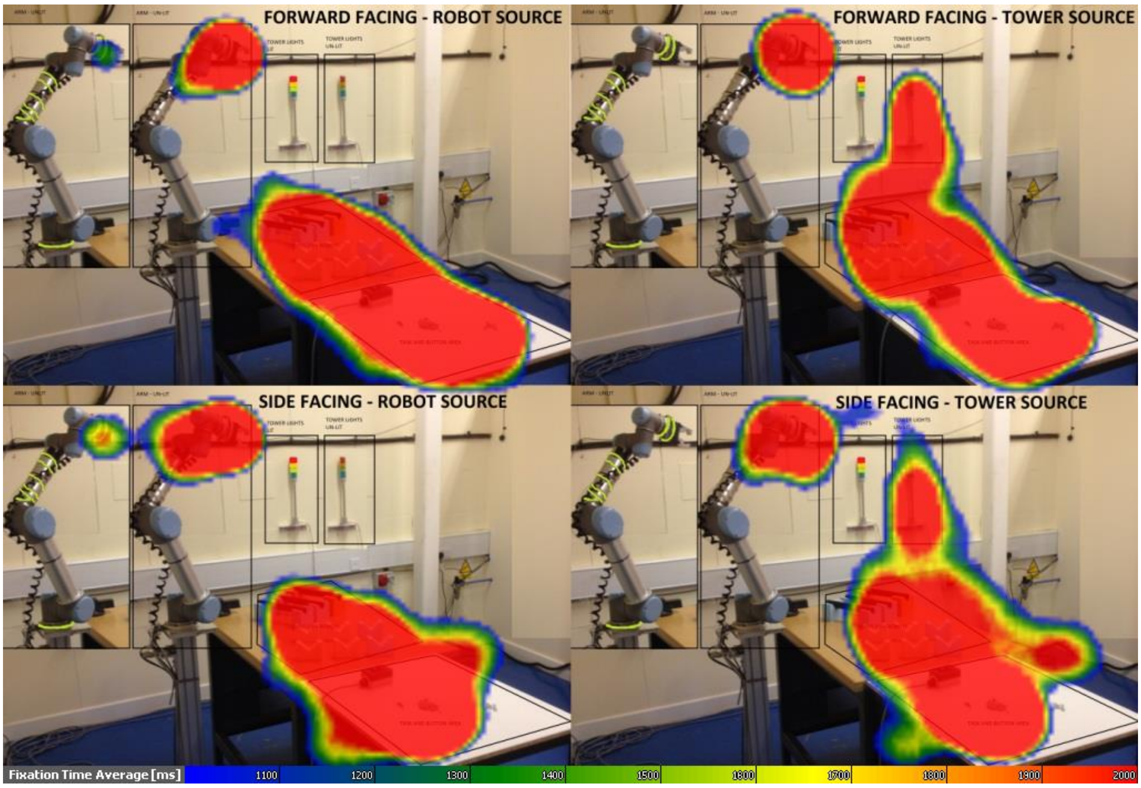


Figure 5-19 – combined average fixation heat map (1000-2000ms)

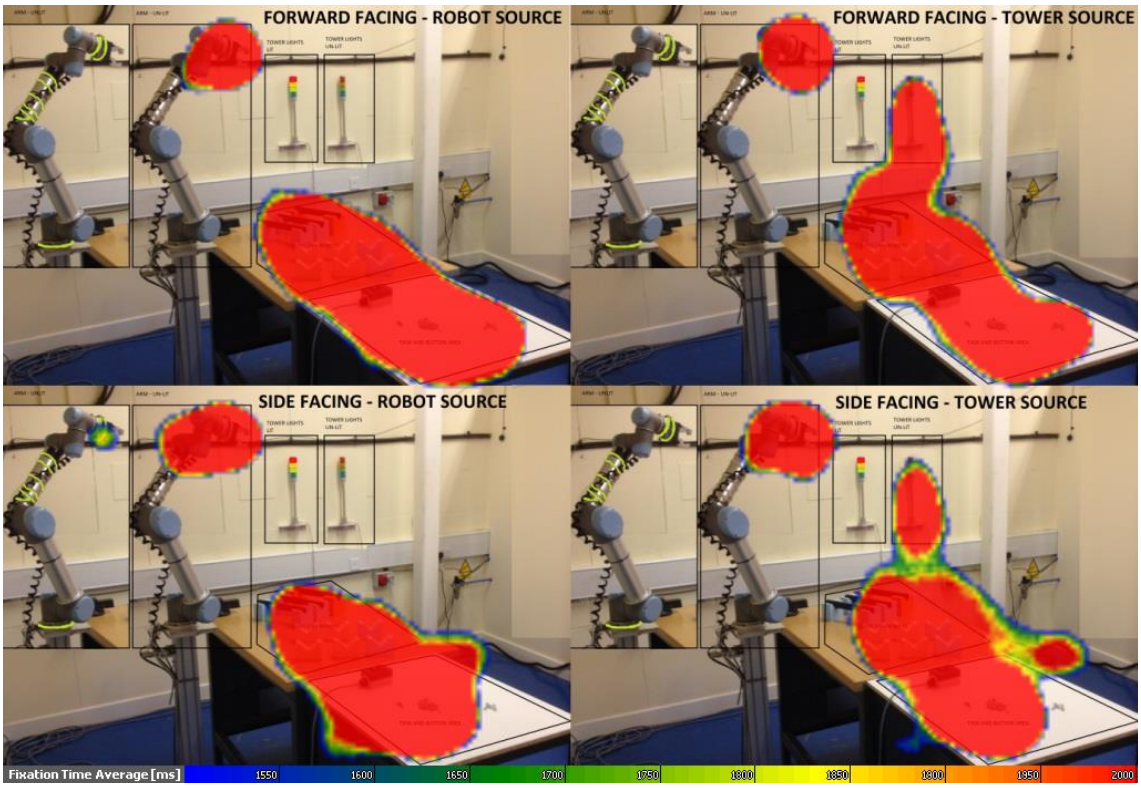


Figure 5-20 - combined average fixation heat map (1500-2000ms)

The results in tables 5-7 & 5-8 show that the fixation time average and fixation count average in the manual work top is higher in the two scenarios with the integrated robot light source than those with the tower light source. In numbers, the fixation time average (manual task bench) of the sideward facing robot light setting is 12445.8ms more than the tower light setting while fixation count is 52.3 times more. In the forward facing scenarios, the robot light setting fixation time average is 9572.1ms over the tower light setting while fixation count is 53.2 times more. It can be an indication of higher allowance of attention on manual task under the integrated robot light condition.

Table 5-7 - fixation time average of four different scenarios

Scenario	Fixation Time Average [ms]					
	Task Bench	Pipes Bench	Tower Unlit	Tower Lit	Arm Unlit	Arm Lit
Side pos - Tower light	28133.4	11966.6	6064.8	694.2	15332.3	0
Forward pos - Tower light	23736.7	26107.2	6975.4	576.1	17350.6	0
Side pos - Robot light	40579.2	16066.3	324.5	0	16567.9	1812
Forward pos - Robot light	33308.8	29111.1	427.1	0	16739.4	2137.8

Table 5-8 - fixation count average of four different scenarios

Scenario	Fixation Count Average					
	Task Bench	Pipes Bench	Tower Unlit	Tower Lit	Arm Unlit	Arm Lit
Side pos - Tower light	150.5	65.5	28.5	4.9	75.7	0
Forward pos - Tower light	129.9	111.6	32.2	3.4	75.6	0
Side pos - Robot light	202.8	85.3	1.9	0	81.3	10.5
Forward pos - Robot light	183.1	141	1.3	0	78.1	12.2

As well as the quantitative measurements were taken, semi-structured interviews were carried out at the end of each experiment. The questions were designed to extract information on user's preference as well as other experimental design related question to enhance future work. One of the question was "How did you find the signal lights? Which one do you prefer? And why?". 12 out of 16 participants preferred the integrated robot signal light where most participants found it better in drawing their attention due to its size. One particular participant found it easier to see the static light tower, but preferred the robot light because it helped robot monitoring. Similarly three other participants preferred the tower lighter, they found it easier because it was a fixed target. However, only one out of these four participants has faster reaction time in the tower light scenarios.

11 participants have some negative comments regarding the comfort level of wearing Eye Tracker during the experiment. 13 out 16 participants have reported that the Eye Tracker obstruct part of their peripheral view. This is justifiable in this experiment, because it resembled a real industrial scenario where operators are obliged to wear safety glasses for personal protection.

The results from the experiment generally show that the integrated robot indication light has a positive effect on the reaction time of participant, significantly less misses of light signals and allows more attention to a manual task and robot arm. It also suggests that the effectiveness of signal light can be affected by its size, position and dynamism.

6 General discussion and conclusion

Industrial robots have been a valuable production tool in boosting factory output, reducing production cost and improving quality. However, flexibility and adaptability are still prime requirements in numerous applications where variability exists. The changes in regulation such as the ISO 10218-2:2011 and advances in robotics technology have enabled robot and human to coexist in the same work space. Nevertheless, an effective interface between human and the robot is key to seamless collaboration. The work presented within this thesis aims to tackle this issue and knowledge gap by developing technical solutions to these problems.

The aim of this research is to develop a human-robot interface for collaborative working in proximity. It was identified that human-robot interface is a research area that could be explored, and that interface should support two-way communications, which is the research motivation that drives the decision to develop a gesture control and an integrated robot indication system for industrial robot. The development was carried out on a collaborative system integrated using components from the current market. The system consists of an industrial robot, control system and sensors for human body tracking. The system architecture was created at the beginning of the project and the system development was separated into two strands: gesture control for industrial human-robot collaboration and advanced robot indication system. As explained in chapter3, the system development is an iterative process which applies to both strands of system development. The research adopted engineering principles as well as user-centred design philosophy in the creation of systems to ensure that human factor is considered. A number of experiments involving human participants were carried out during this research to evaluate the suitability of the developed systems for operating with people.

6.1 Gesture control development

The objectives of this subproject is to develop a gesture control system which enables users to control and teleoperate an industrial articulated-arm robot using simple hand gestures. The system should be user-friendly and intuitive to allow people to be able to command a robot with minimal training. As a result, two gesture control methods have been investigated and developed into different systems which are described as follows.

6.1.1 First iteration of development

At the beginning of the development, two types of gesture control method have been identified to be suitable for communication with industrial robot, and these are gesture recognition and hand following gesture control. Gesture recognition enable user to pose a specific gesture to command the robot, while the hand following gesture control enables the robot to mimic the user's hand and arm movement. For early work, a static pose recognition system was developed for controlling robot movement. A programme was created using C# programming language to receive body tracking data from a Microsoft Kinect and interface with the robot. The idea was a virtual directional control pad where the user activate movement with a closed left palm while point at a specific direction with their right hand. The system was used to carry out two demonstration tasks which include “pick and place” and “peg-in-hole”. Both tasks were carried out successfully but it was concluded the concept should be further developed to a more sophisticated level to suit the target application.

In the next phase, a standardised set of industrial gestures was identified to be in commission in construction industrial where ground worker uses to direct crane operator. A set of ten gestures was designed based these industrial gesture which provides functionality for directional and operational commands for a robot. The Static Pose Recognition (SPR) programme was developed to recognise these gestures using recognition algorithms to analyse Kinect data stream. Some of the directional gestures were identified as impractical at early stages of testing which leaves six gestures for operational command purposes. These gestures were tested using six participants to verify their reliability, and separately the system was tested to be functioning with a robot. The design and evaluation of this system are described in chapter 4.3.6.

On the other hand, Dynamic Hand Motion Tracking (DHMT) programme was developed to study the characteristics of hand following type gesture control. The intention was to develop these systems and make comparison and suggestions for industrial applications. The DHMT tracks user’s hands using a Kinect, the programme maps and feeds hand coordinates to the robot at 30Hz. The accuracy of the system was tested in conjunction with a Leica laser tracker, the laser tracker was used due to its relatively high accuracy and availability during the development. The evaluation shows that the system suffers from poor accuracy and noise in the input data stream. This problem can be rectified by applying appropriate filters such as Kalman Filter to eliminate noise and improve accuracy. However, works have been carried out in the literature shortly after this development showing that errors remain substantial after applying Kalman filter and scaling factor. Du et al (2014) have reported a 3-D error of 3.1mm in their demonstrated task which is significantly higher than typical manufacturing tolerance in high-value production. Furthermore, from a human factor standpoint the issue with lack of human proprioception should be considered. For example, when people carry out an assembly task a number of the body’s sensory inputs are used. We use vision to identify the position of the components and proprioception to position the hands in order to complete the task (Dickinson, 1975; Foster, 2010; Winter et al, 2005). However, in teleoperation of industrial robot the user often view the robot arm from an unnatural viewing angle and the common floor mounted industrial robot arms have different orientation to the human arm. The main perceived benefit of hand following type hand gesture control is the intuitiveness due to control using natural hand movement. As Norman has pointed out, “a poorly designed natural use interface is not natural to use” (Norman, 2010). In an ideal world, this particular type of gesture control can be an optimal solution to robot teleoperation if the robot can be setup in the same orientation as the user’s arm and the user can see the robot arm in a similar perspective as their own arm i.e. through virtual reality glass, but it is not achievable in many manufacturing environment.

A comparison summary is shown in table 6-1, both systems share similar characteristics in terms of usability. As explained above, the DHMT must be setup correctly to have the effect of an intuitive interface. Also the accuracy of the positioning is heavily dependent on the sensor which is a major limiting factor of this type of system. In terms of control, the DHMT can offer control of robot movement, but in order to achieve other commands such as start/stop routine gesture recognition must be incorporate. SPR on the other hand offers greater range of controls, the configuration of these control is also comparably flexible. The accuracy of robot movement is dependent on the resolution of the robot movement which is adjustable, so high positional accuracy can be achieved as demonstrated in the early work. The only downside is the inability to perform path control easily. However, it is possible to guide robot through a path if it is used as a means of teaching robot e.g. to configure movement path via a number of waypoints.

Table 6-1 - comparison summary for SPR and DHMT

	SPR	DHMT
Merits	• Reliable • Intuitive to use • Minimal training required • Many potential applications • Broader range of controls	• Can control robot path in real-time (depends on robot controller) • Intuitive to use (depending on setup) • Minimal training required • Many potential applications

Demerits	• Cannot perform path control	• Reliability and accuracy solely depends on the sensor • Restrictions must to applied to robot speed, movements and working area

An integration has been carried out at the end of this design cycle to shown the potential application of the developed system. The demo incorporated both SPR and DHMT systems to illustrate the benefits of combining different control method into a single system. Face recognition programme has also been integrated into the system to represent a realistic solution. The result is a manufacturing system which accepts multiple operators with different levels of robot control through various gesture control methods. This work has been published in the Industrial Robot journal (Tang et al, 2015).

6.1.2 Second iteration of development

The second iteration of the development continues with the SPR method. The DHMT was abandoned in this case due to its limitations which hamper its applicability in the target applications. This design cycle focuses not only on the functionalities of the system but also the usability. The aim was to create an intuitive and ergonomic gesture control system which can be used in human-robot interaction. In order to achieve the aim, the design process has taken human-centred design approach into consideration. The RULA assessment tool was incorporated during the design of the work station setup. Using this tool, the ideal operating posture and sensor position are calculated. The gestures are also designed to restrict user’s hand movement to minimal which enable people to use the system for prolong period as well as reduce risk of long term work related injury such as musculoskeletal injuries. The developed system enables the user to control a collaborative robot through joint movement and linear movement. The usability of the system was tested using an exploratory usability study by comparing against a state of the art human-robot interface. User satisfactions are similar between the developed system and the touch screen teach pendant. The developed interface performs better in workload, intuitiveness and fulfilment. However, people generally find it harder to use due to the lack of visual and tactile feedback which shows potentials of further development. The developed system was demonstrated in a number of academic and industrial events which include Manufacturing the Future Conference 2014 and 2015, and The Processing & Packaging Machinery Trade Association Show 2015.

Finally, a gesture command system was integrated with a Comau NM-45 industrial robot. The main technical challenges of integration with a heavy duty industrial robot are the different in programming architecture when compare with the development robot and the additional considerations of safety and work cell setup. The system has demonstrated its capability in performing a pick-and-place task fully instructed by the user’s gesture commands. This demonstration has highlighted potential application of this type interface in real applications which include manipulation of component in large scale manufacturing.

6.1.3 Limitations of process and technology

To develop a gesture control interface for human-robot collaboration, the project begins with some preliminary work to develop a “Virtual Directional Pad” controller which was integrated with an industrial collaborative robot. The initial development has exposed a number of limitations with the solution which include practicality of the control, the execution of the movement and speed of execution. These knowledges were used to develop two different types of gesture control system, Static Pose Recognition (SPR) and Dynamic Hand Motion Tracking (DHMT). The SPR was designed to recognition a specific hand gesture pose from a set of predefined gestures derived from industrial crane hand signals. This solution can be used to execute robot commands which include starting/stopping sub-routine and control of movement. The DHMT was designed to control the robot’s motion within its own working envelop. The development of this system was a significant technical challenge due to the nature of the control method. The main functionality is to align the user’s hand position to the robot’s tool centre point (TCP) which requires high amount data transfer between the sub-systems, significant processing power and reliable data from the sensor. Both systems were evaluated and their pros and cons are explained in chapter 6. The developed systems were integrated with a face recognition system to demonstrate their potential applications using a polishing task. For industrialisation of the system, directive gesture command is preferred over gesture motion control for robot movement due to its robustness and reliability.

In the second phase of development, a gesture control system was developed based on the SPR, but this solution has heavier emphasis on human factor consideration in its design process. The purpose of the developed system is not to completely replace a traditional robot teach pendant, but to operate as a complementary input device in an interactive environment. The system is designed to be a secondary input device to reduce travel distance of operator to location of robot teach pendant as well as to reduce risk of musculoskeletal injury from frequent usage. The developed gesture control system was targeting applications in system recovery and error correction in large scale manufacturing environment. The system allows operators to control an industrial robot by moving different joints as well as in linear motion, both without the requirement of significant training. A user evaluation has been carried out which shows that the developed gesture control system has potential to use as an input device for industrial robot control in a human-robot collaboration scene. However, addition features should be incorporated to improve the ease of use and intuitiveness. It is concluded that the usability of gesture control for robot can be significantly enhanced when complemented by a graphical interface with conventional elements which provide user with visual feedback.

Finally, the industrialisation of gesture control was demonstrated on a Comau NM-45 industry robot which was discussed in chapter 4.7. The system has demonstrated the capability of performing a gesture controlled pick-and-place task. This integration has highlighted some of the technical challenges which include complex programme architecture and interface between systems. Nevertheless, it has presented the potentials of gesture interface in industrial applications.

6.2 Robot-Human communication

A human-robot collaborative manufacturing system may require frequent attention from human operator. In this case, effective communication is paramount for seamless operations. Manufacturing plants are complex environment with diverse sound landscape and restriction on wearable device. Thus, majority of factory machines communicate with human users through visual signals. However, these signalling devices were not designed for human-robot collaboration which may have reduced effect. This chapter set out to create a robot status indication system which enable operate to observe robot status at a glance. The aim of the system is to reduce mental workload and improve efficiency of a collaborative task.

6.2.1 Robot gestures

An exploratory study has been conducted investigating the feasibility of using robot generated gesture as a mean to communicate with users. It was logically to consider using the robot arm itself as a signalling device, because it can reduce the visual attention required for users to notice these signals since they should assign some attention in monitoring the robot. An experiment has been carried out with 16 participants to study the effect of these gestures on users' understanding and trust on the robot. The evaluation shows that some participants struggled to comprehend the robot gestures, and most participants hesitate to react to these gestures. Furthermore, these gestures can be difficult to achieve in a realistic industrial setting because the robot will be likely to carry assembly component, which may cause hazard to perform a gesture. This study shows that robot gesture is not the best solution to use as a mean of communication for industrial collaborative robot.

6.2.2 Integrated robot indication light

The second phase of the robot indication system aims to develop an integrated robot indication light system to enable robot conveying messages to the user effectively. The system should allow users to observe robot status at a glance. The proposed concept is a “glowing robot light skin” which covers the exterior of an industrial robot arm. The system was designed with the scope of industrialisation in future development, so it is created targeting the full range of industrial articulated-arm robots. The design process adopted a human-centred design method and a concept validation experiment was designed and conducted. The experiment was carried out with 16 participants. Human factor experimental equipment and method was used to collect both quantitative and qualitative data. The evaluation shows the proposed concept has positive effects on all the measures, which proves this type of indication system has significant potential to be future developed into industrial devices. This experiment setup is designed as the baseline for future experiment. The design concept was tested on a small industrial collaborative robot arm. The user and the robot were positioned in proximity setting. The manual task was keep to the lowest level of simplicity to suit this experiment. The results show that the proposed concept has a number of advantages over traditional tower light and these include faster reaction time, increase task focus, less signal misses and improved ease of monitoring. Based on the experimental results, the benefits of using the proposed system should become more apparent with higher task difficulty, larger robot and greater separating distance between the participant and the robot.

6.2.3 Conclusion

This research investigates the development of potential solution to improve signalling using traditional factory tower light. An exploratory study has been carried out to study users’ understanding of gestures performed by industrial collaborative robot. Participants found some gestures were easier to comprehend than the others. It was concluded that the effectiveness of this method is mainly limited by the physical properties of industrial robot arm and its inherent kinematic differences to human arm. Subsequently, the robot glowing light skin concept was designed and it effectiveness was tested in a comparative experiment against a conventional tower light. Participants were recruited to take part in this experiment where they had to perform a manual task while observing robot movements and the activations of light signal. Quantitative and qualitative data were recorded from the test for analysis purposes. It is concluded that the proposed system has a number of advantage over conventional signal light which suggests that robot manufacturers should consider embedding signal lights on future collaborative robot.

6.3 Future work

A number of suggestions for future work and described as follows:

Gesture control for human-robot collaboration

- Improve accuracy of user tracking data by combining multiple sensors. The integration can involve one or more type of sensors.
- The integration of multiple sensors to expand working envelop of the HRI which eventually enable ubiquitous gesture input in a production environment.
- Real-time calibration of user’s body orientation to enable gesture input from different direction and location.
- To improve robustness of gesture control by limiting gesture input activation by designated user in specific locations and body orientations.
- Future system can include tactile feedback function to improve user experience as well as to improve robustness of control. Contactless tactile feedback can be provided by integrating ultrasonic force fields devices around the control area.
- Provide visual feedback by integration with the state of the art in display technology such as augmented reality or virtual reality device. The visual feedback can provide real-time information and instructions to further reduce training requirement.

Robot indication system – glowing light skin

- Perform comparison experiment on robots at large scales to study the impact of integrated light signals on different scale of work cell.
- Study the effect of signal light position in a collaborative system on users' reaction time, workload, awareness and task performance.
- Study the effect of task difficulty in relation to users' performance on monitoring of robot signal and robot motion.

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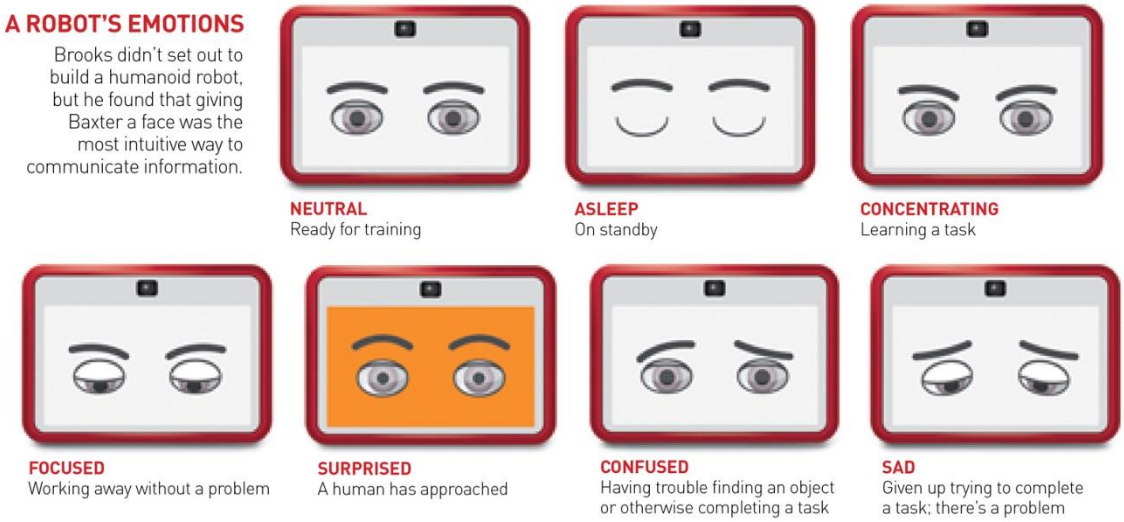
APPENDICES

Appendix A – Literature review

A.1 Effect of digital facial expression

As described in chapter2.5, the Baxter Robot has a robot face to communicate its status with its user as illustrated in figure_apx1 (Rethink Robotics, 2015). Graphic representations of facial expressions which have been broadly used in digital interaction such as e-mail messages and mobile messaging known as Emoticons. These symbols are widely known and commonly recognised among computer-mediated communication (CMC) users, and they are described by most observers as substituting for the nonverbal cues that are missing from CMC in comparison to face-to-face communication (Walther and D'Addario, 2001).



Figure_Apx 1 - Robot's Emotions used in Baxter Robot

The effectiveness of emoticons has been examined in the field of Social Science and Social Psychology (Daantje Derks et al, 2008; Walther and D'Addario, 2001). To (2008) has investigated how emoticons influenced participants' interpretation of instant message statements. He has specifically explored of how different types of emoticons influenced participants' ability to accurately interpret the emotion conveyed by instant message statements and participants' level of certainty about their message interpretations, across "clear" or “unclear” conditions of emotional valence clarity. Experiments have been conducted which involve 121 participants from Canada and the United States. He has concluded the presence of an emoticon led to more accurate performance scores in message interpretation regardless of the emotional valence clarity, compared to the absence of emoticons. On a separate study, it was found that older adults have more positive response toward perceived emoticons than younger adults, and the result also shows older adults can analogise between real faces and emoticons (Hsiao and Hsieh, 2014).

A.2 Equipment for robot safety

There are a number of robotic products on the market which enable human and robot to collaborate in close proximity in a safe manner. Most of these products can be classified as “post collision systems”, typically small robots designed for small scale assembly, requiring smaller loads and levels of accuracy. Good examples of these robots include the Universal Robots UR range and Baxter Robot (Rethink Robotics, 2015; Anandan, 2013). These robots are excellent solutions for small scale handling task, but they are not the ideal solution for large scale manufacturing due to their lack of payload capability and repeatability.

Although the current capability of safety-rated robots may not be applicable to large scale manufacturing, there are a number of other options that can be used to enable human and robot collaboration. Sensitive protective equipment can provide adequate protection for the human operator in collaborative tasks as long as they comply with all the relevant standards as well as being setup correctly according to ISO 10218-2. Below is a list of current safety monitoring devices for industrial automation.

- Safety Camera
- Safety Laser Scanner
- Safety Light Curtain
- Safety Floor Mat

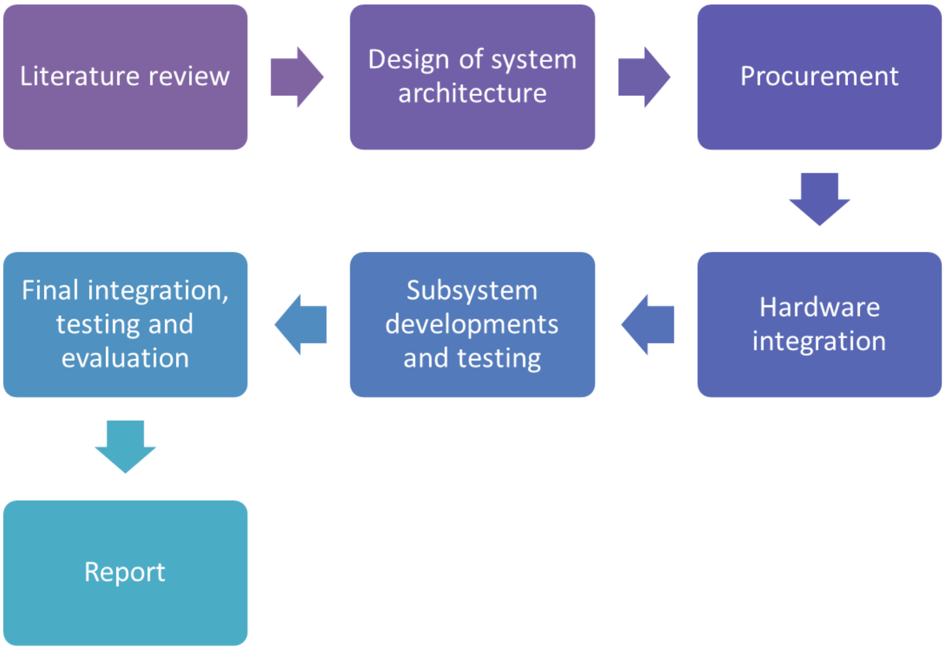
The safety devices mentioned above operate by electronically interacting with a safety controller through safety relay and module. The state of the art safety control systems are capable of handling safety activities among multiple work cells, change of configurations can be completed on a single computer with configurator software, through a graphical interface. Some of the latest safety controllers can be integrated as part of an internal network to coexist with other Industrial Ethernet protocols. That means once devices are physically connected to a safety relay and a network, the organisation of safety device signals can be arranged in a drag and drop manner using a PC based editor program.

Appendix B - Methodology

This chapter describes how this research was carried out and the research method used in conducting this research. This research project follows the scientific methodology detailed in figure_Apx 2. The first phase of this research focuses on identifying the current problem. It begins with a preliminary literature review, which enables the project scope and title to be refined. Once the project scope has been defined, an on-going literature review is performed to identify the ‘state of the art’. The literature review covers of a number of focussed subject areas which include industrial collaborative robot, human and robot cooperation, human-robot interface, industrial robot safety, human recognition in robotics, robotic sensing technology, object recognition, and collision avoidance.

The second phase of the project is to identify system requirements and to carry out system architecture development to these requirements. Subsequently, any hardware and software required should be selected and procured (phase 3) with the support of research of the state of the art. After hardware integration (phase 4), subsystem developments begin with the development of programmes and software which are crucial in enabling the system to function in the designed manner (phase 5). Each subsystem is tested and evaluated before the final integration. This is due to some developments being experimental where the feasibility and usability of the system are to be studied prior to further development.

The penultimate phase of the project is to perform rigorous system testing with the fully integrated system to ensure the system operates in the correct manner. This includes a level of human factors testing and evaluation to measure the usability and functionality of the system. The results of such testing will feed back into the system development and evaluation cycle. Finally, the project will be completed by writing a comprehensive thesis to document the entire research project.



Figure_Apx 2 - different phases of the research

B.1 Literature review

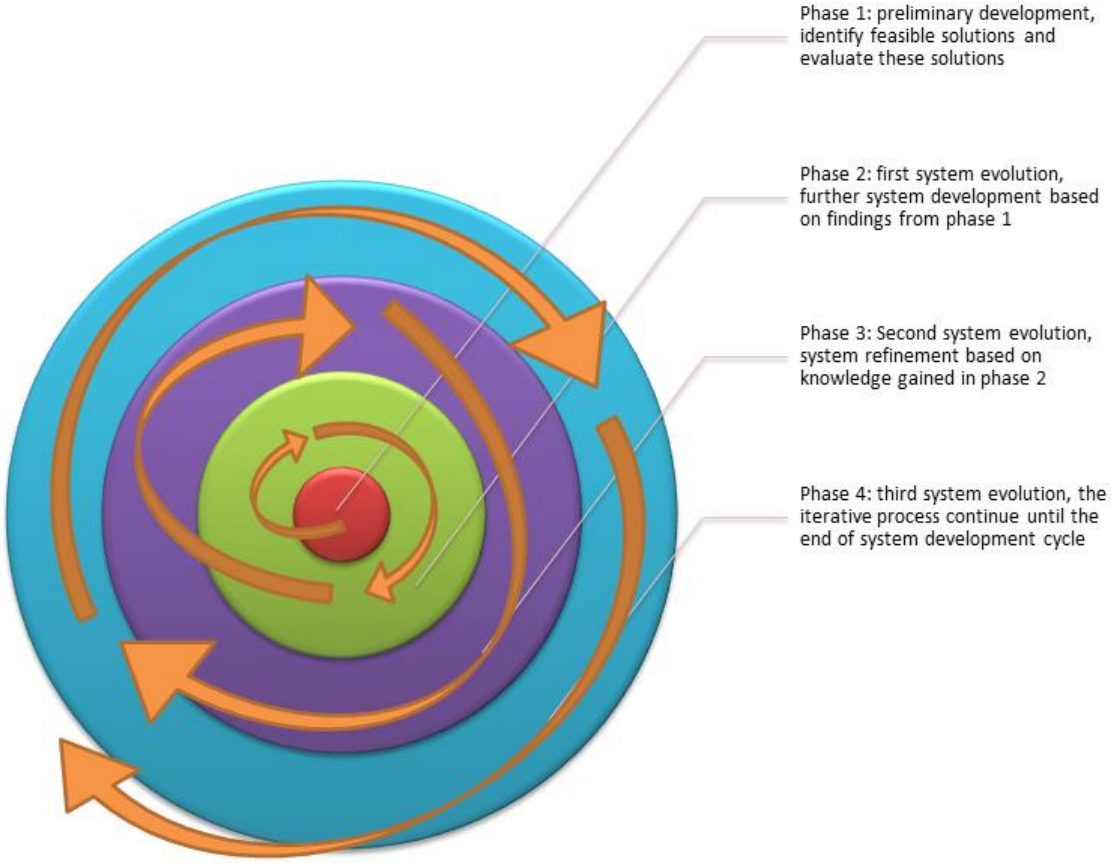
The literature review is divided into three stages. In the first stage, the history of industrial robots and the general concept of human-robot collaborative systems are reviewed. This help identified the current challenges and knowledge gaps in the main research area. The second stage aims to explore knowledge gaps in human-robot collaboration and increase the depth of the literature by investigating into different elements of human-robot collaboration. The final stage of literature review investigates existing techniques and methodologies used in literature which can be applied in the system development and evaluation phases.

B.2 System design methodology

The adopted system development approach was divided in four stages which include investigate, plan, create and evaluate (as shown in figure_Apx 3). The developed system in this context is a human-centred robotic system. The design methodology combines various approaches. There were slight variations in design methods for different sub-system depending on the requirements and the type of system. Nonetheless, these methods were based on the typical system design method which involves the application of human factors criteria in the design process to ensure a good level of usability (figure_Apx 3).

Figure_Apx 3 - system development cycle

The adopted method begins with the “Investigate” phase and then process to “Plan”, “Create” and finally “Evaluate”. However, this process is highly iterative and evolutionary. For instance, the result from the “Evaluate” phase contributes to the “Create” stage to improve the system design, or evaluation result can be used in the “Investigate” phase to begin a new system design of the similar nature. The design of human-centred systems requires that human, financial, and technical issues be considered simultaneously when shaping the technology. This requires a broad range of skills and knowledge of both the technical and human factors. Human factors are considered during initialisation of design proposals, and the design process focuses attention on issues which lie at the intersection of the technology and the human (Kidd, 1992).



Phase 1: preliminary development, identify feasible solutions and evaluate these solutions

Phase 2: first system evolution, further system development based on findings from phase 1

Phase 3: Second system evolution, system refinement based on knowledge gained in phase 2

Phase 4: third system evolution, the iterative process continue until the end of system development cycle

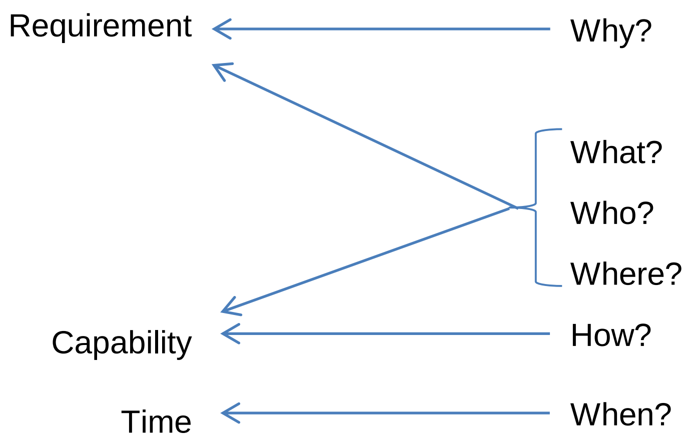
Figure_Apx 4 - an iterative system development cycle

The system development cycle is an iterative process which begins with feasibility study to find potential solutions for further development (figure_Apx 4). At phase1, more than one option can be identified and these options are tested through the preliminary cycle which leads to a comparison study to find the outstanding candidate. At this stage, both technical and human factors suggestions are gathered from literature to establish the plan for system solution. Test results from phase1 are subsequently used in phase2 for further development. The system evolves as knowledge and detail of system design accumulate in previous phase. The cycle continues until the maturity of the system satisfies project requirements. This framework can be applied on most system developments or fitted into existing project management framework such as Technology Readiness Level (TRL) (Mankins, 1995).

The main system consists of two main subsystems which are being developed individually. The development of each subsystem is carried out with the design methodology described above. Some of the sub-projects described in this thesis involve working with other researchers. The reasons for teamwork are to share knowledge and utilise individuals' skills which maximise the output of these projects. The author has been the project lead for these projects and managed the teams.

These projects have adopted the concurrent engineering method (Prasad, 1996) in which a number of tasks were carried out at the same time to minimise system development timescales. Subsystems were designed simultaneously by various team members, and the project lead integrated these subsystems once they were developed to a functional level and compliant to other parts of the system. For example, the development of the Gesture Recognition programme was in line with the development of the communication module, when both modules were developed to a usable state they were integrated into a functional subsystem.

As Mackley et al (2010) explained, System Engineering has to resolve complex problem and it is simply about providing capability to satisfy a need over time, but it is important to define the system requirement, capability and variability over time. Sowa and ZachMan (1992) adopts Rudyard Kipling's 5Ws and H (what, when, where, who, why and how) to address the three areas of System Engineering as illustrated in figure_Apx 5 (Kipling, 1920). The requirement, capability and variability over time can be addressed by the why, how and when respectively. The what, where, and who questions can relate to both the requirement and the capability. Providing the right questions is asked (Mackley et al, 2010). This method was applied in the system development which is described in chapter 3.



Figure_Apx 5 - Mapping of Zachman Framework architectural aspects to areas of System Engineering

B.3 System testing and evaluation

The project consists of a number of system developments. These systems were tested and evaluated using different methods to verify their capability. Most system evaluations in this research have combined qualitative and quantitative methods to develop and improve the system design in the iterative process. The benefits of combining qualitative and quantitative methods have been illustrated in numerous contexts (Cialdini, 1980; Fine and Elsbach, 2000; O'Cathain and Thomas, 2006; Jick, 1979; Weick, 1979; Madey, 1982). Quantitative methods can generate reliable and generalizable data while qualitative methods help understanding the interrelationships of different variables (Steckler et al, 1992).

B.3.1 Data collection

Due to the multi-disciplinary nature of this research, the evaluation involves system testing and human factor testing. Research ethics approvals were obtained from the Cranfield Science & Engineering Research Ethics Committee prior to data collection that involves human subjects. A number of experiments conducted in this research require data collection from semi-structured interview as well as quantitative data from recording devices with test participants. None of the participants involved were rewarded in any way, thus it was necessary to request low risk approvals. Prior to data collection, participants were request to read and sign a participant consent form to ensure they understand the nature of the test and that they agree to be recorded under certain conditions. The author agreed to ensure that the information collected remain strictly confidential through this form, and therefore participant names and personal information are not presented in the data analysis. Only cumulative results are presented in this thesis.