Sheffield Hallam University

College of Business, Technology and Engineering

Department of Engineering and Mathematics

MSc Automation Control and Robotics

Exploring Collaborative Robots Capabilities based on Human Robot-Interaction and Machine Vision

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Abstract

In the last years, the industry has undergone significant development driven by a continual quest for process improvements. The escalating demand for efficient, adaptable, and secure industrial processes has spurred detailed research into the applications and challenges within the realm of collaborative robotics. This study delves into the evolving landscape of collaborative robots (cobots), with a particular focus on the integration of artificial vision in the ABB YuMi robot and its implications for human-robot interaction. The comprehensive literature review provides a profound analysis of collaborative robotics, integrated vision systems, and their applications in the service industry. Subsequent sections elaborate on the specific implementation and configuration of the ABB YuMi robot, emphasising the significance of environmental setup and programming complexities. A meticulous evaluation of the robot's precision is conducted using an integrated vision system. Identifying challenges and opportunities, particularly in human-robot interaction and artificial vision integration, adds depth to the findings. The study concludes by summarising key insights, accentuating technological advances, revealing gaps in current knowledge, and proposing avenues for improvement. Overall, this research contributes a detailed understanding of collaborative robots in real-world scenarios, providing innovative insights and contributing to the ongoing development of collaborative robot technologies in diverse industrial landscapes.

Key words: ABB YuMi, Collaborative Robots (Cobots), Human-Robot Interaction, Machine Vision, Robotics.

Preface

This report describes project work carried out in the College of Business, Technology and Engineering at Sheffield Hallam University between September 2023 and January 2024.

The submission of the report is in accordance with the requirements for the award of the degree of MSc Automation Control and Robotics under the auspices of the University.

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Table of Contents

Table of Figures

List of Tables

Chapter 1

1. Introduction

Robotics emerged from a science fiction plane, where it was believed that having this type of technology was something fanciful (Hockstein et al., 2007) (Kurfess, 2005). The evolution of robotics has been marked by the development of machines that respond to the needs of the industry. As manufacturing processes grow in complexity and scope, the demand for innovative solutions that seamlessly integrate technology with human experience has never been more pressing. In response to this need, collaborative robots (cobots) have emerged as a transformative force in industrial automation, allowing not only to increase productivity but also to guarantee a higher degree of worker safety (Matheson et al., 2019).

A major advance is the development of collaborative robots that work alongside humans as opposed to traditional industrial robots which operate in confined, fenced space. (Ge et al., 2020) This paradigm shift has been driven by a combination of technological advances, declining costs, and increasing recognition of the potential benefits of human-robot collaboration. According to a report by Markets and Markets (2023), the collaborative robot's market is projected to reach $6.8 billion by 2029, with a Compound Annual Growth Rate (CAGR) of 34.3% between 2023 and 2029.

Although the collaborative robot has high security when working with people around it, its capabilities have not been used to the maximum. Therefore, to increase the efficiency of cobots, integrated vision systems need to be implemented. These systems are essential for cobots to adapt to dynamic and unstructured environments.

In this context, this thesis explores the convergence of integrated vision systems, its practical implications for industrial processes and its impact on efficiency and safety in industrial environments. By analysing the interaction between these technologies and industrial operations, it is intended to provide a solid basis for decision-making in the implementation of advanced vision systems. Likewise, it seeks to identify key challenges and opportunities that can be replicated in future projects, both practical and investigative, to optimize processes while minimizing risks in the industrial environment.

1.1. Aim

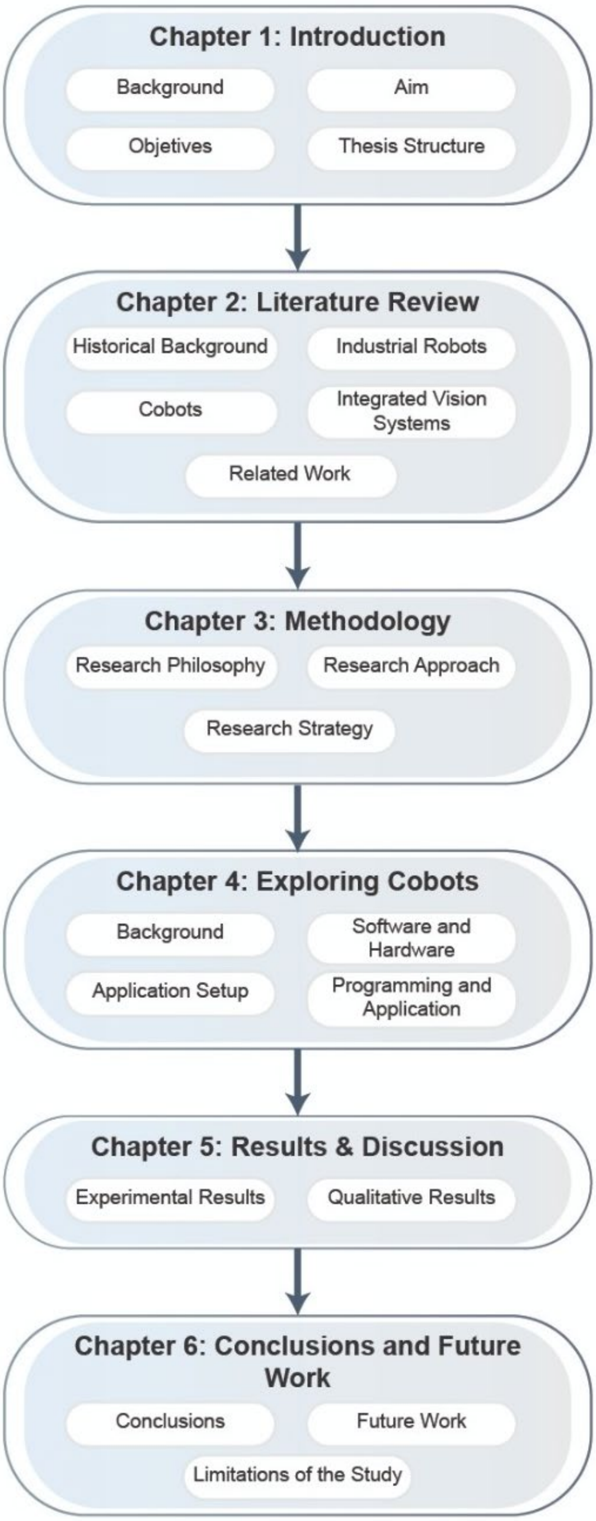
This research aims to investigate and understand the capabilities of collaborative robots, particularly focusing on their interaction with humans and the integration of machine vision. A collaborative robot is undergoing testing to determine its ability to efficiently employ machine vision while simultaneously maintaining functionality in other tasks.

1.2. Objectives

1. Analyse the state of the art in collaborative robotics, integrated vision systems, and their applications in service industries through literature review and conceptual development.
2. Implement and configure a collaborative robotic system, using a prior thesis as a case study, with a focus on environmental setup and programming.
3. Examine the specific capabilities and functionalities of the ABB YuMi robot in the context of real-world scenarios.
4. Evaluate the accuracy of the ABB YuMi 14000 robot when using the integrated vision system.

5. Investigate the challenges and opportunities associated with collaborative robots, emphasising human-robot interaction and machine vision integration.

1.3. Thesis Structure



Chapter 2

2. Literature Review

2.1. Historical Background

The evolution of robotics as a scientific field has been constant throughout human history, adapting to changing social needs (García et al., 2007). Since its inception, man has been curious about machines capable of imitating human movements. Even in ancient civilizations, such as ancient Greece, they studied narratives and concepts related to machines designed to emulate human actions, preparing the scenario for future technological innovations.

In 1921, the Czech writer Karel Capek premieres his work Rossum's Universal Robots (RUR), where the term robot is mentioned for the first time, which derives from the Czech word "robota," which means servant or worker (Barrientos et al., 2007). Thus, introducing the concept of robotics to the culture and collective thinking of the society of the time, catalysing a transformation in the perception and understanding of the relationship between humans and machines.

However, according to Hockstein (2007), Isaac Asimov was the maximum promoter of the term robotics in his novel Runnaround. Asimov not only proposed autonomous machines, but also described ethical guidelines for their behaviour called the Three Laws of Robotics. These laws emphasized the importance of prioritizing human safety and well-being in the development and deployment of intelligent machines.

The Industrial Revolution was an important moment for the popularity of technologies (Sotelo et al., 2007), as during this period, it experienced significant growth and contributed to its subsequent expansion in the 20th century. Specifically, in 1942, the first laws of robot behaviour were established, marking a crucial point in the history of robotics **Invalid source specified.**. This period was characterized by the convergence of advances in electronics, computer science, and engineering, paving the way for the creation of advanced mechanical devices. Additionally, prominent pioneers such as Alan Turing, John von Neumann, and Norbert Wiener played a fundamental role in laying the theoretical foundations of artificial intelligence (Mühlenbein, 2009). Thanks to these advances, not only did it drive the expansion of various scientific domains, but it also stimulated the creation of innovative robotic devices with applications in a wide range of industries and sectors. Robotics began to play an increasingly important role in automating industrial processes and enhancing people's quality of life.

The history of robotics is inextricably linked with the broader historical narrative of industrialization. As humanity embarked on a journey through the various stages of the Industrial Revolution, the emergence and evolution of robots became a symbol of innovation and progress. The era of the Industrial Revolution was divided into four stages. The first industrial revolution, taking place in the 18th century, was characterized by the use of water and steam to drive the mechanization of machines, marking the first revolution in manufacturing (Ostergaard, 2017). This enabled the creation of factories with production lines and mass assembly.

The Second Industrial Revolution, occurring in the late 18th century, was distinguished by the adoption of electricity, replacing steam engines with electrically powered motors (Sherwani et al., 2020). Over time, in the third industrial revolution that occurred in the late 19th century, computers and automated machines took on the responsibility of further automation and enhancing the capacity of manufacturing and assembly lines (Tan & Rajah, 2019). This advancement led to unprecedented levels of efficiency in industrial production. However, with the advent of Industry 4.0, also known as the fourth industrial revolution, an even more advanced concept in the industrial domain is presented. This term created in Germany in 2011 (Morrar et al., 2017) reflects the evolution of automation through digitalization and the interconnection of production processes.

The fourth industrial revolution is characterized by the seamless integration of smart technologies, including the Internet of Things (IoT), artificial intelligence, and cyber-physical systems. The core principle of Industry 4.0 lies in creating intelligent, connected, and data-driven ecosystems that redefine traditional production processes (Morrar et al., 2017) (Sherwani et al., 2020). Figure 2.1 shows the four stages of the industrial revolution.

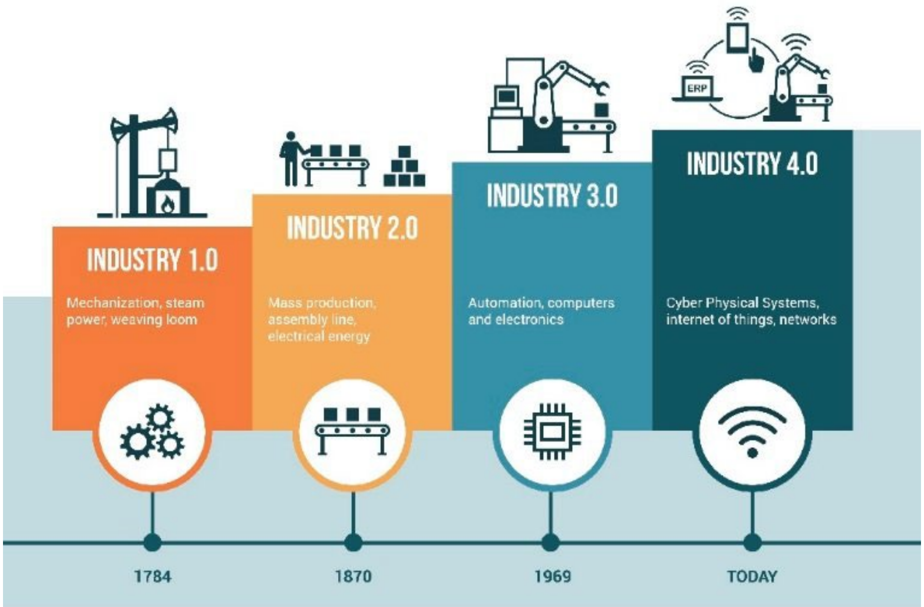


Figure 2.1 Four stages of the industrial revolution (Kovács et al., 2019).

Currently, robotics has swiftly evolved in response to the growing needs of industries and the convergence of rapid technological advancements in automation, engineering, energy storage, artificial intelligence, and machine learning. This transformation has pushed the capabilities of robots to a point where they can assume tasks that were once carried out by humans. Since 2010, the global stock of industrial robots has more than doubled, and engineering and machine learning innovations portend an accelerated adoption of robots in service sector occupations, driving productivity and economic growth (Oxford Economics, 2019).

2.2. Origins of Industrial Robots

Clearly, the concept of robots is no longer confined to science fiction but has been actualized through human ingenuity and passion for technological advancements. Although the first automated industrial processes began with the industrial revolution, Gaspareto & Scalera (2019a) mention that the first industrial robots appeared in the 1950's. Due to the third industrial revolution, robots have developed into machines capable of not only imitating or performing repetitive movements, but also performing tasks that are dangerous and harmful to humans (Billard & Kragic, 2019). In this context, robots became indispensable for accelerating and enhancing industrial processes. While this marks a significant milestone, a crucial question arises: What criteria must a robot fulfill to seamlessly integrate into an industrial process? The answer lies in its ability to be automated, programmable, and capable of movement within the Cartesian coordinate system (Ge et al., 2020). As a result of this principle, many industrial robots have been developed throughout history, each contributing significantly to industrial progress. Throughout the remainder of this chapter, the evolution of industrial robots from their origins to the present day will be described.

2.2.1. *Industrial Robotics' Evolution and Pioneers*

Zamalloa et al. (2017) proposed that the evolution of industrial robotics can be categorized in five generations, but within this section only the first four will be mentioned. A dedicated section will be allocated to the discussion of the fifth generation as it constitutes one of the focal points of this project.

1. First Generation: This generation spans from 1950 to 1967. The paramount of this period is the creation of the robot Unimate (see Figure 2.2), which was created by George Devol and Joseph Engelberger in their company Unimation (Gasparetto & Scalera, 2019b). According to Singh et al. (2013), Unimate was hydraulic actuated, and it was used for material handling and spot welding in the automotive industry. The company that opted for this robot was General Motors, which used it to extract parts from a die-casting machine. Unimate helped to enhance efficiency in industrial settings by automating tasks that were previously performed manually. This led to faster production cycles, increased throughput, and reduced production times resulting in long-term cost savings for industries.

Figure 2.2 Unimate Robot (Gasparetto & Scalera, 2019a)

2. Second Generation: This generation spans from 1968 to 1977. The integration of microprocessors and sensors led to the robots of this generation being programmable machines that can react to their external environment. In fact, these robots were the first to use servo controllers to perform both point-to-point motion and follow a trajectory on a path (Gasparetto & Scalera, 2019a). Furthermore, a notable feature of these robots was the use of Programmable Logic Controllers (Plc), which allowed them to perform more complex tasks. However, they were not yet able to adapt easily or quickly to various functions because each robot had its own software, and it was not easy to reprogram the algorithms they already had. Therefore, these robots were limited to specific applications since using the same robot for different tasks was very difficult.

During this generation, Victor Scheinman, a mechanical engineering student, invented the Stanford Arm in 1969 (see Figure 2.3) (Moran, 2007). The Stanford Arm was the first electric actuated robot, employing six electric motors for power and control, eliminating the need for hydraulic or pneumatic systems. Additionally, this robot was equipped with six joints, which means six degrees of freedom (DOF), and several sensors to measure its position and velocity, such as tachometers and potentiometers. As a result, the robot was able to perform intricate movements and manipulate objects precisely.

Figure 2.3 Stanford Arm. (Stanford University, 1994)

In 1974, Scheinman created the Vicarm robot arm in his new company, Vicarm Inc. Compared to the Unimate robot, this robot was smaller and lighter, enhancing its characteristics (Kurfess, 2005). Moreover, the Vicarm was used in assembly lines, where heavy loads were not required. In 1977, Unimation acquired Vicarm Inc, and they used the technology of the Vicarm to build the Programmable Universal Machine for Assembly (PUMA) (see Figure 2.4). The PUMA has long been considered a model of such designs, and its kinematics are the basis for robotic education and research (Marsh, 2004). Therefore, numerous textbooks on robotics use the PUMA to illustrate controller design and motion principles.

Figure 2.4 PUMA Robot. (Gasparetto & Scalera, 2019a)

Shepherd and Buchstab (2014) mentioned that the company Keller und Knappich Augsburg (KUKA) built the robot Famulus in 1973, which was the first robot to have six electromechanical-driven axes. The Famulus was not only used in the industry but also in laboratory automation, performing tasks like pipetting and sample handling. One year later, Cincinnati Milacron, a machine tool manufacturer, introduced a robot dubbed T3 (see Figure 2.5), which was prominently featured in numerous automotive plants, particularly in Volvo facilities in Sweden. T3 emerged as the first commercially marketed minicomputer-operated industrial manipulator.

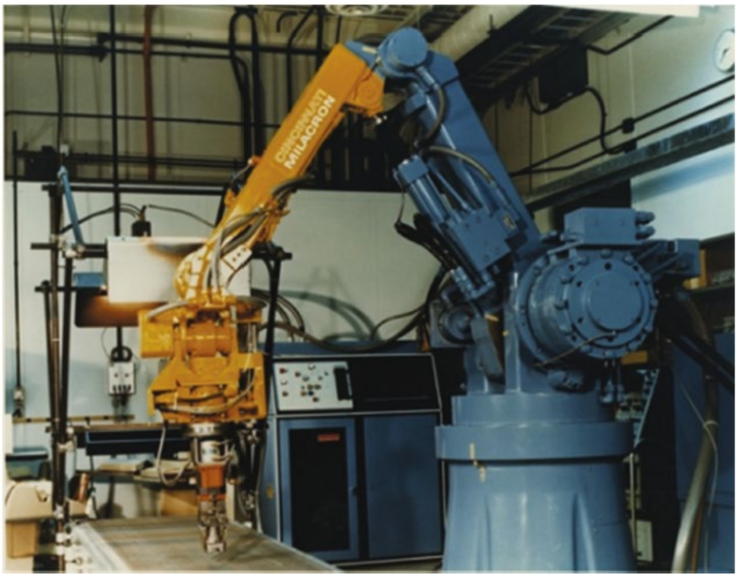


Figure 2.5 The Cincinnati Milacron T3 robot. (Gasparetto & Scalera, 2019b)

Finally, within this generation it can be mentioned one of the leading robotics companies known at that time as Allmänna Svenska Elektriska Aktiebolaget (Asea), which years later would merge with Brown, Boveri & Cie to create the company Asea Brown Boveri (ABB) (ABB, n.d.). In 1974, ABB developed the first all-electric industrial electric robot called IRB-6 (see Figure 2.6), which was controlled by a microprocessor (Rooks, 1995). The novelty of this robot was that it could follow continuous paths, which would make it suitable for tasks such as arc-welding or machining. The IRB series robots were characterized by their orange colour and were so successful that their production continued for more than 20 years (Gasparetto & Scalera, 2019b).

Figure 2.6 IRB-6 (Motat, n.d.)

3. Third Generation: This generation dates from 1978 to 1999. Authors such as (Zamalloa et al., 2017) and (Maeda, 2012) mentioned that the era robots started in 1980. According to Rifkin (1995), trillions of dollars were spent by companies around the world on automated equipment specially in assembly lines. Zamalloa et al. (2017) mentioned this led to an 80 percent increase in demand for industrial robots compared to previous years. As a result, robots became increasingly prevalent in various industrial sectors, automating a wide range of activities, including painting, soldering, handling, and assembly (Wallen, 2008).

Within this generation, it stands out that industrial robots exhibited high interaction with human operators and their surroundings. This was thanks to the fact that they began to incorporate modules of vision, sound, or both (Gasparetto & Scalera, 2019a). Furthermore, according to Zamalloa et al. (2017), companies that were dedicated to creating robots began to develop their programming languages. For example, companies such as Unimation, Fuji Automatic Numerical Control (FANUC), and ABB created Variable Assembly Language (VAL), Karel, and Rapid respectively. Programming options were versatile, allowing operators to program the robots either online, using a teach box with a keyboard, or offline by connecting to a PLC or PC. This allowed robots to possess a certain level of self-programming capabilities, allowing them to adapt to different tasks and improve their flexibility.

Following the history of robots, in 1982, Professor Makino from the University of Yamanashi in Japan developed the concept of the Selective Compliance Assembly Robot Arm (SCARA). This concept aimed to create a robot with a limited number of degrees of freedom (3 or 4), a cost-effective design, and a configuration specifically tailored for the assembly of small components (Barrientos et al., 2007). The utilization of the SCARA robot was primarily centred around companies engaged in the production of electronic goods. Japan strategically leveraged the distinctive features of the SCARA robot, contributing significantly to its emergence as a leading exporter of electronic products . The Figure 2.7 shows one of the first prototypes proposed by Professor Makino.

Figure 2.7 The initial SCARA robot prototype (Gasparetto & Scalera, 2019b).

Despite the significant progress that the robotics industry had made, there was still a need for robots capable of performing fast and precise tasks. This pushed researchers to develop prototypes applying different physical and mathematical models. This is where the idea of the Delta parallel robot was born, which is inspired using parallelograms. The first patent for this delta robot appeared in 1992, created by researcher Reymond Clavel at the Ecole Polytechnique Fédérale de Lausanne (EPFL) (Bouri & Clavel, 2010). The delta robot introduced a unique three-parallel link design that offered exceptional speed, precision, and payload capacity compared to traditional serial robots. Its compact and lightweight design also suits tight spaces and high-speed applications. Delta robots are characterized by three identical arms or struts connected to a common base and sharing a single central axis. Each arm features a prismatic joint at the base and a rotary joint at the end effector (Pierrot et al., 1990). The parallel structure allows for precise and rapid motion, making delta robots well-suited for pick-and-place tasks, assembly, and packaging applications. In Figure 2.8, it can be seen a diagram of the first Delta robot.

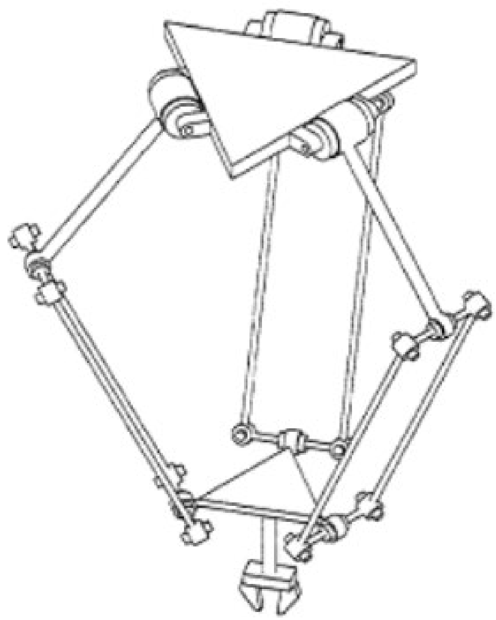


Figure 2.8 Delta Robot Schematic (Poppeová et al., 2011)

The Swiss company Demaurex used the Delta robot for first time in the food processing industry in 1992 for packaging pretzels and other food items. Figure 2.9 illustrates how six Delta robots worked within a work cell to fill trays with pretzels, as stated by Gasparetto & Scalera (2019a).

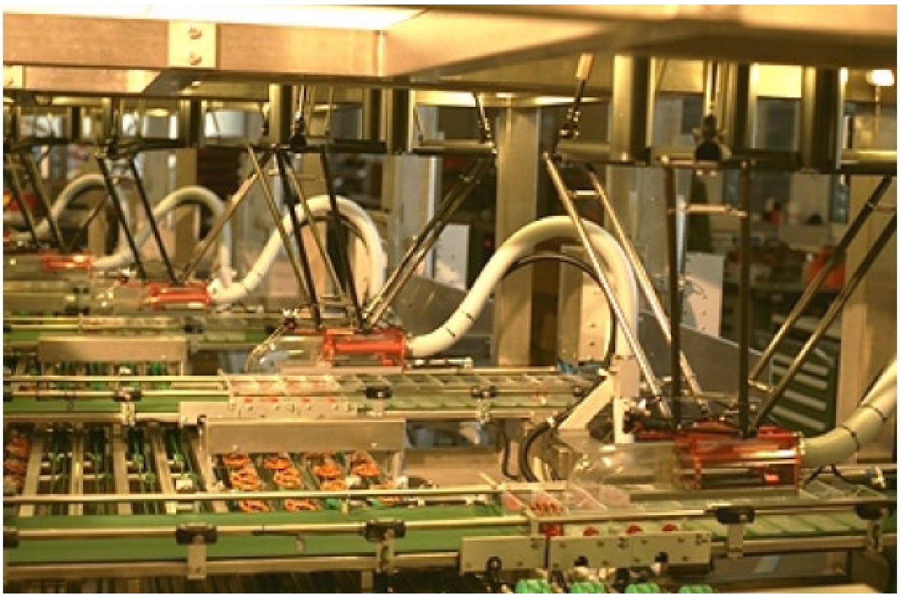


Figure 2.9 Delta robots automate pretzel packaging at Demaurex work cells. (Gasparetto & Scalera, 2019a)

Finally, it can be highlighted that in this generation ABB bought one of the patents for Delta Robots and built its robot called IRB 340 Flex-Picker (see Figure 2.10) in 1999. According to Brantmark & Hemmingson (2001), Flexpicker was used in picking tasks with the same or greater flexibility than a human operator. For example, it was able to make 150 picks per minute, which is twice as fast as a human operator. This robot already included several units and tools that helped it perform tasks even on a mobile conveyor. These systems include vision, dedicated software, vacuum components, etc. Therefore, these types of robots have already begun to revolutionize the industry even more and it can be already noticed the technological difference that these robots brought compared to those of past generations.

Figure 2.10 ABB IRB 340 Flex-Picker robot. (Gasparetto & Scalera, 2019a)

4. Four Generation: This generation spans from the year 2000 to 2017 as mentioned by Zamalloa et al. (2017). In this generation, there is no longer the emergence of new models of industrial robots but rather it consists of intelligent robots and improved versions of past generations. However, Grau et al. (2021) mention that a new philosophy within industries characterizes this generation. As observed in past generations, industrial robots are automata that require a specific space to work with established safety standards. For instance, each robot operates in an isolated cell, assigned a specific task; each of these cells is connected to manufacturing processes through conveyor systems (Stengel et al., 2010). This ensures that industrial robots operate precisely and safely, avoiding any harm to human operators. The traditional lack of autonomy in industrial robots, constraining their ability to adapt to unforeseen actions, historically posed safety challenges. However, in this generation, a notable shift occurred, leading to the emergence of automata with the capability to partially share spaces with human operators. This transformation not only reflects technological advancements but also signifies a shift towards more flexible and

adaptive industrial practices. In essence, the fourth generation brings a convergence of intelligence, collaboration, and adaptability to redefine the landscape of industrial robotics.

In 2002, the American company iRobot created the first automatic robot vacuum cleaner called Roomba (Yatmono et al., 2019). Although this robot was no longer focused on industry, the technology it had already made it an intelligent robot. Elara et al. (2014) mention that the first version of this robot consists of two motors for locomotion and sensors that allow it to detect its surroundings so as not to collide with obstacles in front or below. Therefore, The Roomba robot can be considered one of the first robots that could perform a task within a space where human beings lived and not represent a danger to them. In the Figure 2.11, it can be seen the first version of the Roomba Robot created by iRobot.

Figure 2.11 Roomba- Automatic Robot Vacuum Cleaner (The National Museum of American History, n.d.)

Regarding the industrial sector, humanity was going to witness the introduction of collaborative robots better known as cobots. Basically, the concept of these robots was developed to break down the barriers between humans and industrial robots (Grau et al., 2021). Cobots, such as the Universal Robots UR5 (see Figure 2.12) and UR10, have gained popularity for their ability to work alongside human operators safely, offering flexibility in manufacturing processes. Furthermore, the era saw the integration of advanced technologies such as machine learning and artificial intelligence into industrial robots, improving their adaptability and autonomy (Zamalloa et al., 2017). Companies like Boston Dynamics introduced dynamic and agile robots like the Spot robot, showing new possibilities in automation (Zimmermann et al., 2021). The focus on human-robot collaboration, enhanced intelligence, and versatile applications characterizes the evolution of industrial robots in the contemporary era.

Figure 2.12 Universal Robots UR5 (WiredWorkers, n.d.)

In a nutshell, the evolution of industrial robots has been rapid, with over 40 years of research and development. Robots can be used in small or large factories to replace humans in repetitive and hostile tasks, and they are immediately adaptable to changes in demand that occur at any time during production. The future of robotics will also focus on improving mobility, dexterity, and autonomy while maintaining a high level of human interaction and control. Most of today's robots are used in industrial applications such as assembly, welding, palletizing, pick-place, etc. Nevertheless, there are other types of applications that have greatly advanced conceptions and morphologies of robots. These innovative robots, known as collaborative robots, extend beyond merely working alongside humans. They incorporate cutting-edge technologies such as machine vision and artificial intelligence, representing a transformative milestone in the realm of robotics.

2.3. Collaborative Robots (Cobots)

In recent years, the industry has experienced remarkable transformation, driven by the increasing demand to enhance efficiency and productivity while maintaining cost-effectiveness (Bejarano et al., 2019). Within this framework, the incorporation of robots is undoubtedly the most viable option. These robots offer a solution in terms of speed, adaptability, versatility, and resilience (Brantmark & Hemmingson, 2001), allowing for the optimization of production processes in any industrial facility.

However, in today's industry, the need goes beyond simply making machines work efficiently. The emphasis is on promoting close collaboration between automation and human work, thus facilitating the creation of collaborative work environments where both robots and human operators can work safely (Peshkin & Colgate, 1999). This gives rise to collaborative robots (cobots), which, unlike traditional industrial robots, adhere to the laws proposed by Isaac Asimov, focusing on safety and cooperation. Cobots represent a new era in industrial automation by incorporating technologies that enable safe and efficient interaction with human workers, thereby reinforcing the synergy between advanced machinery and human skills (Knudsen & Kaivo-Oja, 2020).

2.3.1. History of Cobots

The idea of cobots was first suggested in the late 1990s at Northwestern University by Edward Colgate and Michael Peshkin. The main objective was to solve the limitations of industrial robots. The original conception of cobots was the creation of an innovative category of robots designed to collaborate closely with humans. This is for the purpose of providing assistance and supporting various tasks, complying with the relevant security measures (Dr. George & George., 2023).

In 1996, Colgate and Peshkin invented the first cobot, demonstrating its main differentiator from existing robots in the world, the collaboration between human and machine controlled by a computer, focusing on improving the capabilities of the operator instead of replacing the human. In their initial phases of development, the first cobot prototypes were characterized as passive mechanical devices without active drive. This is why the devices relied on guidance provided by humans to carry out movements and execute specific tasks. Additionally, one of the most important aspects was the repeated focus on safety, as the cobots remained motionless unless directed by a human operator. This precaution was intended to minimize the risk of accidents and injuries during interaction with the devices (Bicchi et al., 2008).

The advancement of force and torque sensors, vision systems and other sensing technologies gave rise to the new generation of collaborative robots with advanced capabilities. These were characterized by their autonomy and receptivity to their environment. Thus, allowing cobots to adjust their activity based on sensor inputs and environmental conditions, ensuring efficient and adaptive task performance (Dr. George & George., 2023).

2.3.2. Definition of Industrial Collaborative Robots

The interpretation of cobots has varied across different contexts, leading to distinct definitions based on the application. According to Bitonneau et al. (2017), “cobots work alongside humans physically in shared workspaces”. Cobots are described by Peshkin and Colgate (1999) as robots that interact directly with humans in completing a task. Furthermore, Salunkhe (2023) empathizes that cobots require advanced sensors and actuators to avoid collisions and detect obstructions. This is mentioned in the International Organization for Standardisation / Technical specification (ISO/TS) 15066:2016, which establishes safety requirements for collaborative industrial robots and their work environments (British Standards Institute, 2016). It complements existing safety standards for industrial robots, such as ISO 10218-1 and ISO 10218-2, by addressing the unique risks associated with close human-robot collaboration.

On the other hand, the purpose of an industrial collaborative robot is to enable seamless interaction between humans and robots in industrial settings, fostering a dynamic manufacturing environment in which humans and robots can work together in harmony (Pons, 2013). Moreover, this device is designed to reduce mental and physical strain on workers while assisting them in accomplishing tasks. Besides assisting, industrial cobots support human operators by lifting and moving production loads, tracking assembly lines, and ensuring loads are placed quickly, precisely, and safely (Restrepo et al., 2017). The table below displays examples of collaborative robots being deployed in the industry based on their main specifications.

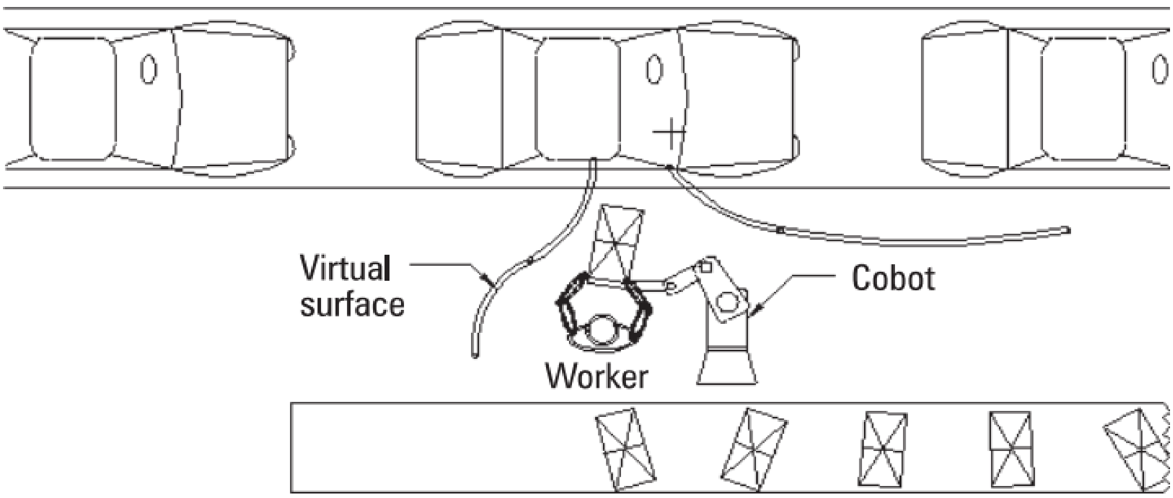
Table 2.1 Examples of industrial collaboratives robots in the industry (Hentout et al., 2019).

Robot	Company	Specifications	Applications
URC 3, 5, 10	Universal Robots	6-dof in single arm; Collision detection; Robot stops upon collision; Speed reduction to 20%	Packaging; Palletizing; Food handling; Pick-and-place parts in optimized production flows
Robonaut	NASA	Stereo-vision camera; Infrared camera; High-resolution auxiliary cameras; Miniaturized 6-axis load cells; Force sensing in joints	International space station; Space robotics

Yumi IRB 14000	ABB	Dual-arm body (7-dofeach); Action resumption only by human through remote control; Collision-free path	Mobile phone; Electronic and small parts assembly lines
LBR iiwa	Kuka	Contact detection; Velocity and force reduction on collision; Single arm with 7-axis	Machine tending; Palletizing; Handling; Fastening; Measuring

2.3.3. Cobots in Human-Robot Interaction

Hentout et al. (2019) highlights the evolution of industrial robots over the last 30 years, emphasizing their adaptability, flexibility, and integration of sensors for various production tasks. Recently, technological advances have enabled robots to share workspaces with humans and become collaborators, replacing humans in repetitive and hazardous tasks (Hvilshøj et al., 2009). However, robots may not be able to fully complete certain tasks if they are too complex or too expensive. As a result, it is the most flexible and affordable solution if a human worker assists and shares the task-execution with robots. In this context, Hentout et al. (2019) emphasizes the importance of Human-Robot Interaction (HRI) in ensuring safety and



effective collaboration. As shown in the below Figure, a human-robot interaction is illustrated.

Figure 2.13 A cobot and a human worker work together. (Peshkin & Colgate, 1999)

According to Schmidtler et al. (2015), HRI can be described as all ”forms of interactions between humans and robots”. Human-robot interaction is described by Fang et al. (2014) as the process of translating task descriptions into motions compatible with robot capabilities. Humans and robots can communicate and perform tasks seamlessly with the support of this aspect, which facilitates effective collaboration between them.

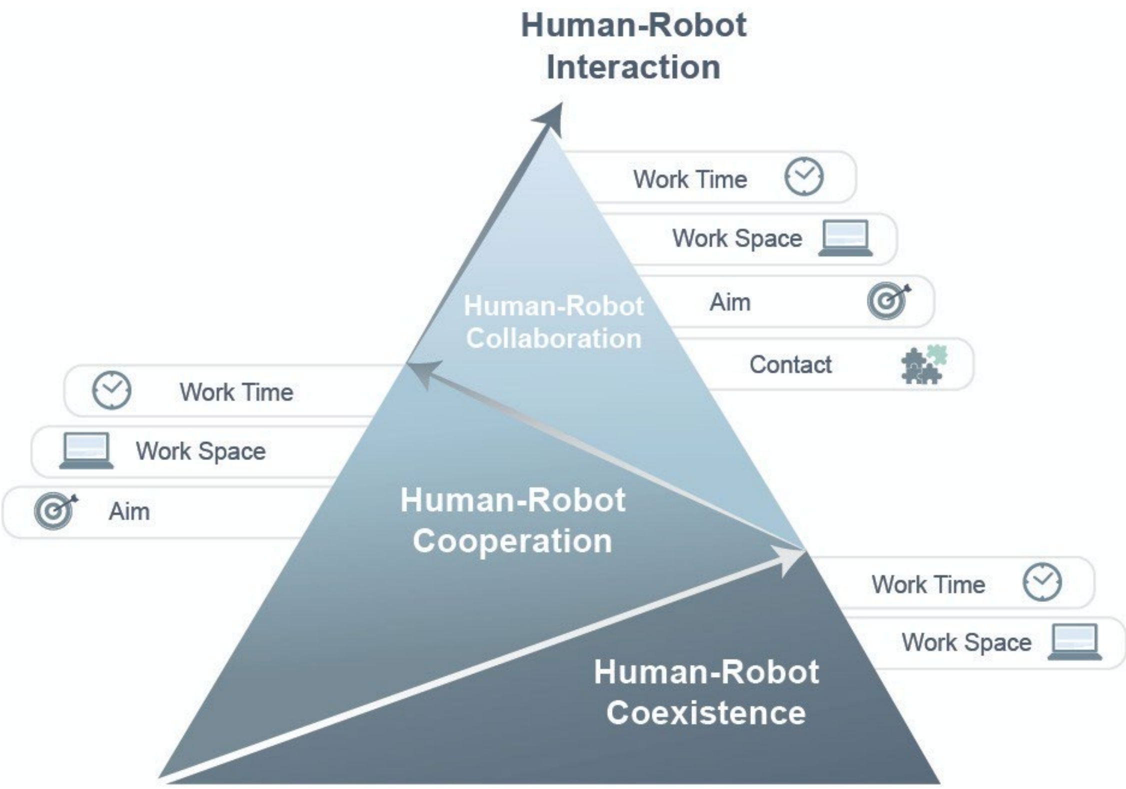


Figure 2.14 Levels and factors in Human-Robot Interaction

Human-Robot Interaction covers the dynamic relationship between humans and robots, involving various aspects such as cooperation, coexistence, and collaboration. Figure 2.14 categorizes HRI based on four crucial factors: workspace, working time, aim, and contact (Schmidtler et al., 2015). For instance, human-robot coexistence (HRCx) occurs when humans and robots occupy the same space or environment at the same time but have different goals (Schiavi et al., 2009), while human-robot cooperation (HRCp) involves both entities working towards the same objective within the same time and space (Wang et al., 2019). Finally, human-robot collaboration (HRC) goes beyond cooperation, emphasizing a more interactive and coordinated effort. In collaborative scenarios, humans and robots actively engage in joint tasks, exchanging information and adapting their actions based on real-time input. Therefore, cobots are specifically designed to facilitate such close interaction between humans and machines (Pang et al., 2021).

According to Segura et al. (2021) and Zhang et al. (2021) the HRI levels can also be described as four different scenarios (see Figure 2.15). This classification is described as follows:

- **Independent:** This category includes situations where humans and robots work completely independently of each other, performing separate tasks in the same workspace without any interaction or need for coordination (Cesta et al., 2016).
- **Sequential:** In this scenario, humans and robots perform tasks one after the other, with the robot taking over after the human has completed their job or vice versa. There may be some interaction to pass on information or prepare the workspace for the next stage, but there isn't continuous collaboration (El Zaatari et al., 2019).

- **Simultaneous:** This category involves humans and robots working together on the same task at the same time, but in distinct roles. For example, a human might operate a machine while a cobot assists with feeding materials or performing subtasks. There is coordination and communication, but each entity maintains its own autonomy (Helms et al., 2002).
- **Supportive:** This involves the robot providing support or assistance to the human while they perform their primary task. Although the robot may hold objects, adjust tools, or provide information, it is not directly involved in the major task. The focus is on enhancing human capabilities and making their work easier or safer (Segura et al., 2021).

It's important to note that these categories are not always mutually exclusive. A collaborative robot system might involve elements of independent, sequential, and simultaneous operation depending on the specific task and phase of work. However, this way of looking at HRI helps to understand the degree of interdependence and joint action within human-robot partnerships.

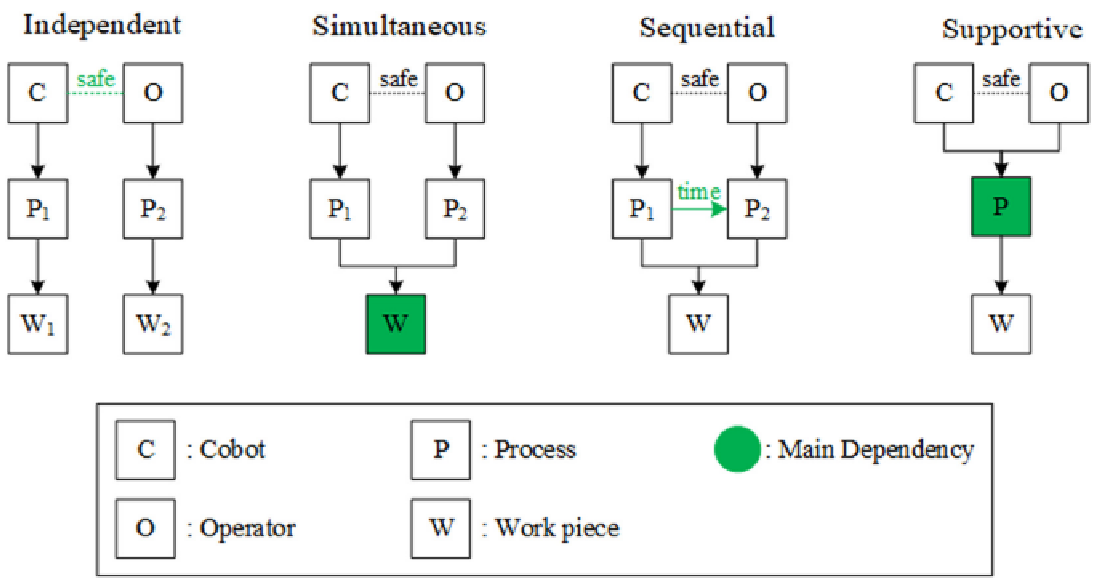


Figure 2.15 Human-Robot Interaction Levels (El Zaatari et al., 2019)

2.3.4. Safety standards for Collaborative robots

According to the Oxford English Dictionary (n.d.), safety means 'the state of being protected from or guarded against hurt or injury'. In the robotics and HMI literature, safety transcends mere physical protection. It is a multi-layered tapestry woven from foresight, design, communication, and trust, ensuring human-robot partnerships thrive without risk (Santis et al., 2008). In the research presented by Vicentini (2021), he identified physical interactions between robots and humans, classifying them as either desired or undesired contacts or collisions. However, safety extends beyond mere collision prevention; it involves the identification, assessment, and mitigation of potential risks and hazards associated with the interaction between humans and robotic systems. Designing for safety in collaborative workplaces is crucial to ensure the well-being of human workers and the optimal functioning of the collaborative robot (cobot).

In this context, technical specifications and standards have been established to guide companies and individuals in prioritizing the safety of both humans and robots. These standards are formulated by the International Organization for Standardization (ISO). Specifically, the International Federation of Robotics (IFR) outlines safety standards for the industrial robotics sector, including ISO 10218-1, ISO 10218-2, and ISO/TS 15066. In the non-industrial or service robotics sector, safety standards are governed by the ISO 13482 standard (IFR, n.d.). It's important to note that the ISO 13482 standard is not considered in this thesis.

2.3.4.1. ISO 10218

The ISO 10218-1/2 standards establish primary safety requirements for industrial robots, covering design, construction, safeguarding, and integration. They act as the basis for safe robot operation, defining risk assessment procedures, protective measures, and testing guidelines. describes the requirements and limitations related to a robot's behaviour when it collaborates with an operator (ISO 10218-1, 2011). In the meantime, ISO 10218-2 specifies the requirements for robot system safety when employed within HRC (ISO 10218-2, 2011).

2.3.4.2. ISO 15066

This technical specification zeroes in on collaborative robots (cobots), defining specific safety requirements for their design and operation in shared workspaces (ISO/TS 15066, 2016). According to Hjorth & Chrysostomou (2022), these guidelines emphasize the proper procedure for restricting speed values. This limitation guarantees that the force and pressure limits stay within the specified threshold of pain sensitivity for humans during interactions with robots, with the goal of averting harm in the context of Human-Robot Interaction (HRI). As a result of these specifications, the following four levels of control modes (see Figure 2.16) can be established:

- **Safety-rated Monitored Speed (SMS):** This refers to a control mode in which the robot's speed is monitored to ensure that it remains within safe limits during human-robot interactions. If the speed exceeds predefined thresholds, the robot's motion is either slowed down or stopped to prevent potential harm.
- **Hand-Guidance (HG):** Hand guidance allows a human operator to physically guide the robot by hand. This mode is often used for teaching or programming the robot in a collaborative setting. The robot responds to the operator's movements, and its motion is controlled manually.
- **Speed and Separation Monitoring (SSM):** This control mode involves monitoring the speed of both the robot and the human worker and ensuring a safe separation distance between them. If the system detects a decrease in separation or unsafe conditions, it can trigger safety measures, such as slowing down or stopping the robot.
- **Power and Force Limitation (PFL):** Power and force limitation involves setting limits on the maximum force or power exerted by the robot. This helps prevent injury in case of contact between the robot and a human. If the force or power exceeds predefined limits, the robot's motion is limited or stopped to avoid harm.

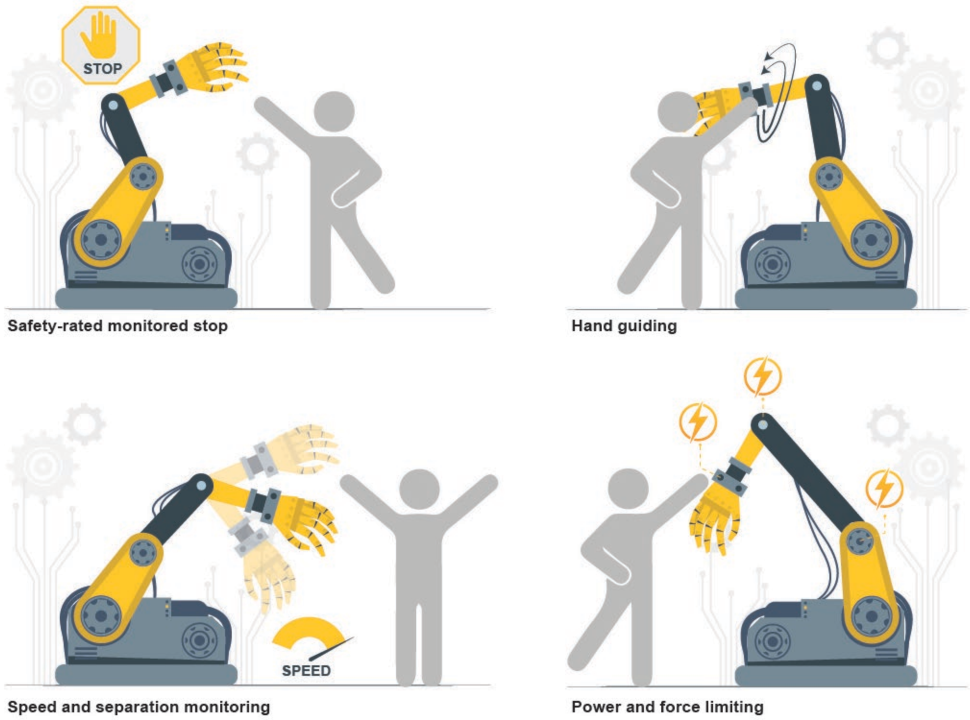


Figure 2.16 Visualization of the four different control levels (Villani et al., 2018)

2.3.5. Programming Cobots Methods

Programming involves guiding robots through a systematic and strategic approach to execute a wide range of tasks with precision and adaptability. Based on Fogli et al. (2022), this approach involves determining the robot's path and the specific points to be followed, including related actions such as open-close gripping, picking-placing objects and so on. The primary objective is to explicitly instruct the robot without adversely affecting its productivity. This process is usually carried out by skilled engineers and software specialists in robot programming. Traditionally, two general interfaces or techniques are employed for programming robots, although the choice depends on the specific application (Vicentini, 2021). Researchers also explore alternative interfaces for robot programming such as multi-modal interfaces and enhancement of reality (Billard et al., 2016) (Argall et al., 2009) (Bischoff & Kazi, 2004).

The traditional approaches include on-line programming, like lead-through, walk-through and programming by demonstration, and off-line programming (OLP) with software tools such as digital twins. OLP aims to reduce downtime in robot programming by eliminating the need for the robot to be physically present. Note that these programming methods are applicable to cobots and industrial robots as well. The figure below provides an overview of the programming methods utilised with collaborative robots in the current state of the art.

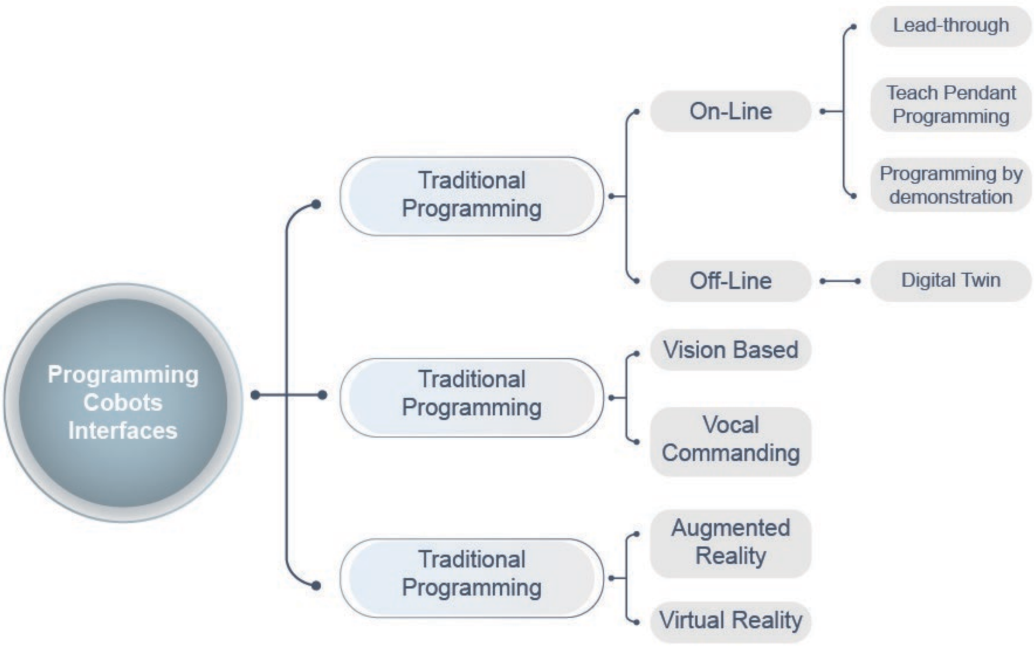


Figure 2.17 Programming methods utilised with collaborative robots.

2.3.5.1. On-Line programming

On-line programming refers to the process of programming a robot while it is actively operating or connected to its controller in the real-world environment (Fogli et al., 2022). This approach allows for immediate adjustments and modifications to the robot's behaviour, and the programming changes take effect in real-time. Moreover, on-line programming is accomplished through teach programming methods. These methods involve guiding a robot through a sequence of motions using a teach pendant or similar input device that allows operators or programmers to interact with the robot and input instructions directly (Nof, 1999).

Teach programming utilizes three basic algorithms: point-to-point, continuous path, and controlled path motion, an extension of continuous path control with additional parameters for speed and acceleration control (Nof, 1999). In point-to-point control, the robot moves directly between specified points without consider an intermediate path (Kelly et al., 1997), while continuous path control allows the operator to guide the robot along a continuous path rather than specifying individual points. Controlled path motion is an extension of continuous path control but provides additional features for controlling all join motion such as speed, acceleration, and deceleration along the path (Nof, 1999). These teach programming methods provide a flexible and intuitive way for operators to instruct robots, particularly in dynamic environments or for tasks requiring precision.

Lead-through and teach pendant programming are interactive methods for instructing robots in on-line programming. Lead-through programming involves a human physically guiding the robot through desired motions, and the robot learns and replicates these movements (Nof, 1999). Lead-through is commonly associated with continuous path control. On the other hand, teach pendant programming employs a handheld device, often resembling a pendant, to input instructions to the robot (Villani et al., 2018). The operator can manually control the robot's movements, input specific points, or guide it along paths, allowing for a more controlled and precise programming process (Morely & Syan, 1995). Teach pendant programming is linked with point-to-point motion and controlled path motion. To sum up, both methods offer a hands-on and intuitive way to program robots, with lead-through focusing on physical guidance and teach pendant programming utilizing a handheld interface for instruction.

The advantage of on-line programming is its responsiveness to dynamic conditions and the ability to adapt the robot's actions in real-time. However, on-line programming may require the robot to be temporarily taken out of production during the programming phase.

2.3.5.2. Off-line programming

Off-line programming (OLP) is a programming methodology in robotics where the robot is programmed and simulated in a virtual environment, separate from the actual robot and its physical workspace (Mitsi et al., 2005). Instead of programming directly on the robot itself, engineers and programmers use specialised software known as Digital Twins to create and test robot programs offline. The completed program can then be transferred to the physical robot for execution.

One key advantage of off-line programming is efficiency. According to Fogli et al., (2022) this method is used to prevent unnecessary downtime in industrial processes and machinery. It also enables engineers to experiment with different scenarios and optimize robot trajectories without the limits of the physical workspace (Pan et al., 2012). Nevertheless, simulating the real environment accurately is often complex or nearly impossible using the cobot programming software. Therefore, after programming, tests are typically necessary to identify and correct errors or adjust trajectories as needed.

Another significant benefit of off-line programming is safety. According to Khoukhi (2002), programming and testing in a virtual environment reduce the risk of accidents or collisions that could occur when programming directly on the physical robot. Engineers can identify and rectify potential issues in the virtual space before the program is implemented on the real robot. This contributes to a safer and more controlled programming process, particularly important in environments where robots collaborate with human workers.

Unfortunately, implementing off-line programming often requires specialized software tools and simulation environments, which can be expensive to acquire and maintain (Villani et al., 2018). Additionally, the initial investment in training personnel to use these tools and adapt to the off-line programming workflow can contribute to increased costs (Hwang et al., 2016). Small or budget-constrained enterprises may find the financial aspect prohibitive, limiting their ability to adopt off-line programming solutions.

2.3.6. Benefits and Drawbacks

Collaborative robots, or cobots, have emerged as transformative tools in the realm of industrial automation, offering a unique synergy between human workers and robotic systems (Cohen et al., 2022). Unlike traditional robots confined to safety cages, cobots are designed to work alongside humans in shared workspaces, encouraging a new era of collaboration (Wannasuphoprasit et al., 1997). Additionally, these robots are capable of handling repetitive and physically demanding tasks, allowing human workers to focus on more complex and valuable tasks (Paliga, 2023). Nevertheless, like any transformative technology, cobots come with their fair share of both benefits and drawbacks that need careful consideration.

2.3.6.1. Benefits

- **Boosting Productivity and Efficiency**: Cobots can take over repetitive, tedious tasks, freeing human workers for higher-level activities. Their tireless nature, precision, and ability to operate 24/7 significantly increase production volume and output. A study by (Fager et al., 2020) found that cobots can increase time efficiency by up to 50% in tasks such as supporting the sorting process in kit preparation.

- **Enhanced Safety and Ergonomics:** Cobots prioritize safety with features like force limiting and built-in collision detection, reducing workplace injuries and fatigue associated with strenuous tasks. Bragança et al. (2019) mention that this cobots can handle tasks that involve heavy lifting or repetitive motions, reducing the strain on workers and preventing musculoskeletal disorders.
- **Increased Flexibility and Adaptability:** Cobots are designed to be easily reprogrammed and redeployed, offering flexibility in production processes and adaptability to changing production demands. Tamas & Murar (2019) implemented a baxter-type cobot with a Manufacturing execution system (MES) for the vertical integration of manufacturing layers. The authors highlight the flexibility and adaptability of the cobot to work with other technologies.
- **Improved Quality and Consistency:** With their precise movements and tireless work ethic, cobots minimize manufacturing errors and ensure consistent product quality, leading to enhanced customer satisfaction (Heo et al., 2023).

While collaborative robots present numerous advantages, their integration is not without challenges. Addressing these drawbacks is crucial for maximizing the benefits of cobots and ensuring a harmonious human-robot collaboration. Concerns range from initial investment costs and programming complexities to potential job displacement and the need for robust safety protocols. Navigating these challenges will be imperative as industries increasingly adopt collaborative robots to stay competitive and efficient in the evolving landscape of automation.

2.3.6.2. Drawbacks

- **High Initial Investment Costs:** The upfront cost of purchasing and implementing cobots can be significant, especially for small businesses. This cost-barrier can hinder wider adoption despite the long-term benefits. The average cost of a cobot can range from $20,000 to $50,000, with additional costs for installation, training, and maintenance (Weckenborg & Spengler, 2019).
- **Job Displacement Concerns:** The fear of losing jobs to automation remains a potent concern. While cobots are designed to complement human work, careful planning and reskilling initiatives are crucial to mitigate potential job losses. However, Dahlin (2019) through the regression models presented in his research, found no evidence indicating that robots are displacing workers or stealing jobs from any types of occupations.
- **Programming Complexity :** Programming cobots for specific tasks may pose a challenge, requiring skilled technicians or engineers to ensure optimal performance and task accuracy.
- **Safety Protocols and Regulations:** Ensuring the safety of human workers working alongside cobots requires adherence to stringent safety protocols and compliance with industry regulations, adding complexity to implementation (British Standards Institute, 2016) (ISO *15066:2016).*

2.4. Integrated Vision Systems

Visual perception plays a crucial role in the behaviour of numerous living species, particularly in the context of humans (Kragic & Vincze, 2009). This provides beings with valuable information about the environment, allowing them to function and interact intelligently (Berthold Klaus, 1986) and effectively in their daily activities. Similar to how human vision is essential for understanding the world around them, robot vision systems are a tool that enhances the ability of cobots to autonomously carry out tasks, such as inspecting the workspace, locating objects, recognizing patterns, and responding to changing environmental conditions (Martinez & Pobil, 2010; WiredWorkers, n.d.). This contributes significantly to improving productivity and accuracy, not only in industrial environments but also in domestic and corporate environments. Thus, facilitating faster and more reliable execution of various operations.

Within the evolving landscape of automation and robotics, the assistance of vision systems, becomes increasingly vital. While human vision remains fundamental for perceiving and navigating the world, robot vision systems extend these capabilities to machines. This collaborative integration amplifies the adaptability and efficiency of cobots, facilitating seamless interaction with their surroundings. As cobots are deployed in diverse environments, the integration of machine vision technology equips them with the ability to process visual data, make informed decisions, and execute tasks with precision (Upadhyay et al., 2023).

In this context, machine vision emerges as a crucial technological field enabling computers and systems to gather information about their surroundings through the analysis of digital images, videos, and visual inputs (Xiong, 2008). This process involves interpreting visual data using algorithms and specialized software, allowing machines to understand their surroundings in a manner similar to human perception. Functions such as barcode reading, defect detection, traceability, sorting processes, optical verification, vision robotics, and more (Javaid et al., 2022), have enabled artificial vision applications to overcome significant limitations in their ability to operate in industry, showcasing their extensive benefits (Cognex, n.d.). The effective integration of computer vision into robotic systems becomes an essential component to enhance their perception and action capabilities in the surrounding environment. The next figure illustrates the key features of the computer vision concept.

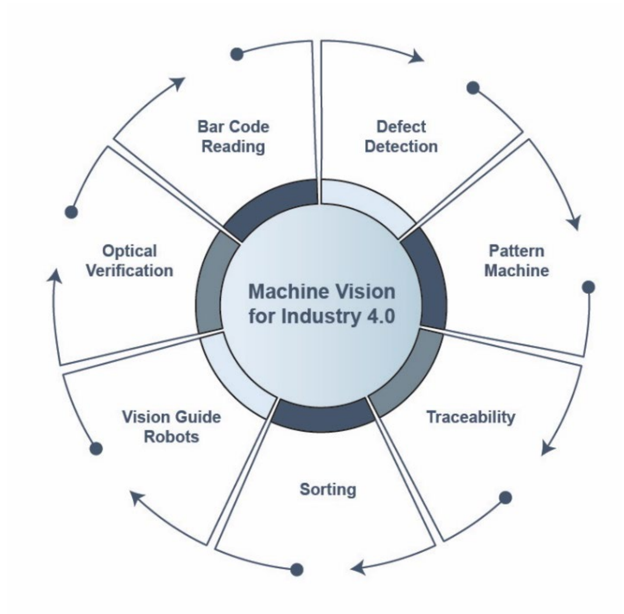


Figure 2.18. Main characteristics of machine vision concept (Javaid et al., 2022)

According to Kragic & Vincze (2009), the connection between computer vision and robot vision reveals a fundamental difference. While computer vision focuses on interpreting a scene from individual images or a fixed camera position, robot vision involves a system-level perspective. In the robotic context, vision becomes one of several sensory components collaborating to accomplish specific tasks. This characteristic of robotic systems, known as embodiment, reflects the influence of body properties on perception functions, similar to biological systems.

In this context, computer vision is not treated as an isolated entity but as an integral part of a more complex system. The figure below illustrates the key features of the computer vision concept and how it connects with integrated vision robotic systems, highlighting the importance of considering vision as a crucial element for the effective interaction of robots with their environment. The combination of these technological approaches unlocks new possibilities for improving machines' perception and responsiveness in various industrial applications and beyond.

2.4.1. Benefits

- Flexibility y adaptability

Machine vision enables cobots to adapt easily to unexpected changes in the environment, seamlessly adjusting to new surroundings without limitations, and handling each application with maximum precision. This includes selecting, sorting, and picking each piece without losing track of location and orientation. (Hardin, 2021) (Eurobots, 2020).

- Higher Quality

The ability to visually analyse each object allows the robot to identify imperfections that are often overlooked by human labour. The camera magnifies the image, facilitating a detailed and precise inspection, contributing to a faster delivery of high-quality products and services (Cadecobots, 2021).

- Productivity

By working with an almost negligible margin of error, production increases, and production time is significantly reduced, allowing for greater productivity in less time (Eurobots, 2020). This not only enhances operational efficiency but also decreases waste and contributes to a quicker delivery of products or services (Javaid et al., 2022), positively impacting customer satisfaction and competitiveness in the market.

- Tighter process control

The incorporation of integrated vision systems in the production line enables real-time monitoring, implying continuous surveillance at each stage of the manufacturing process. This capability allows for a constant flow of feedback to refine process control. Smart cameras play a role in inspection, generating results that are transmitted to both the control system and computer systems overseeing various cameras. By combining these capabilities with predictive process management techniques, visual inspections not only focus on product quality but are also crucial for tracking key metrics and analysing patterns in these measures (Javaid et al., 2022).

2.4.2. Applications

In the context of automated production, image processing systems through industrial cameras have become essential components, playing a fundamental role in data collection for Industry 4.0. As more companies embrace automation technologies, the integration of artificial vision solidifies as a central technology in production and quality control. The applications of artificial vision in the industry are diverse, ranging from content inspection and object identification to pattern recognition and electronic component examination. Thanks to their effective implementation in smart factory environments, computer vision systems are highly efficient, enhancing both human and digital performance (Javaid et al., 2022).

2.5. Related work

2.5.1. Case study one

The research proposed by Yang et al. (2023) focuses on automating Small and Medium-sized Enterprise (SME) production through a collaborative robot (cobot) system enhanced by a learning-based vision. The key challenges in implementing cobots in SMEs, such as increased visual perception, diverse task handling, and rapid deployment, are addressed through a comprehensive automation framework. The learning-based vision system employs YOLOv5 for object detection and a Convolutional Neural Network cascaded with a Support Vector Machine (CNN-SVM) for quality control.

A multi-functional gripper system is designed to perform various operations without tool changing, adapting to environmental changes. In addition, a digital twin of the robotic system is developed to transfer data between the virtual world and the physical world, which is employed by robot operation system (ROS). Onsite testing with an SME partner confirms the system's ability to accurately perform automated production, with potential applications across various SME productions.

The discussion emphasizes the successful development and validation of the automation framework, particularly highlighting the robustness of the learning-based vision system in object detection and quality control. As a result, the researchers proposed future work that includes validating the system for direct human-robot collaboration and refining the digital twin to account for complex robot structures and interaction dynamics. In providing continuous improvements, the research demonstrates its dedication to advancing the field of collaborative robotics and automation in SME production.

2.5.2. Case study two

Rautiainen et al. (2022) focuses their research on developing a Multimodal Interface for Human–Robot Collaboration, addressing the need for intuitive communication between humans and robots in Industry 4.0. The proposed solution, Multi-Modal Offline and Online Programming (M2O2P), introduces a software component that enables communication with a robot using predefined yet configurable hand gestures. The study evaluates M2O2P within a smart factory use case in the SHOP4CF EU project, highlighting the effects of gesture personalization on user workload and the component's usability. The following table presents the summary of their research.

Table 2.2 Summary of Multimodal Interface for Human–Robot Collaboration

Topic	Multimodal Interface for Human–Robot Collaboration
Key Findings	1.M2O2P's gesture personalization reduces both physical and mental workload, as evidenced by NASA-TLX assessments. 2.The overall usability of M2O2P is high, with a System Usability Scale (SUS) score of 79.25. 3.Gesture recognition accuracy is measured at 99.05%, comparable to state-of-the-art applications.
Methodology	1.The study includes user tests in a smart factory setting, involving 10 participants with a focus on evaluating gesture personalization effects on workload. 2.Evaluation tools include SUS for overall system usability, NASA-TLX for workload assessment, and a stand-alone test case to assess gesture recognition accuracy. 3.The research employs statistical tests like Welch's t-test and Mann–Whitney U test to analyse results.
Contributions	1.M2O2P offers a gestural interface for human-robot communication, supporting a smart glove as a sensor device. 2.The solution provides a GUI for enhanced user experience, including task descriptions, gesture examples, and functionalities such as calibration and testing.

	3.M2O2P is designed to be context-aware, modularly integrated with other systems, and adaptable to changing gesture recognition devices.
Conclusions	1.The study proposes M2O2P as a versatile interface for natural input, highlighting its potential for context-aware applications. 2.The accuracy of M2O2P's gesture recognition supports its effectiveness, with opportunities for future improvements using AI and ML techniques. 3.While personalized gestures show lower mental and physical workload, careful consideration of task design is essential for optimal performance.

2.5.3. Case study three

Bejarano et al. (2019) focuses on implementing a human-robot collaborative assembly workstation using the ABB YuMi robot. The primary objective is to create efficient workspaces where robots and human operators can collaboratively work on interrelated processes. The research successfully demonstrates a real scenario of collaborative interaction between a cobot and a human operator, highlighting the potential advantages and challenges of implementing cobots in industrial facilities. The experiment shows that the ABB YuMi cobot can execute a human-robot collaborative assembly process with acceptable precision, accuracy, coexistence, and simultaneity parameters without causing harm to human operators.

The article details the design, implementation, and validation of the collaborative assembly workstation. The assembly process involves the ABB YuMi cobot interacting with a human operator to assemble a product box as part of a larger-scale process. The study evaluates the precision, accuracy, coexistence, and simultaneity parameters of the collaborative process. Additionally, the authors discuss the major concern of process times, emphasizing the balance between providing better working conditions for operators and maintaining productivity. The research also highlights the importance of collecting and analysing process execution data to address uncertainties in human intervention times and explores the potential benefits of using cobots as a source of data about human behaviour in manufacturing.

The paper contributes by challenging traditional perceptions of cobots and presenting a collaborative process that breaks away from sequential actions, showcasing simultaneous and coexistent tasks performed by both robots and humans. Moreover, the authors emphasise that the current definition of cobots follows standard robot features, focusing on safe operations for humans without the need for physical barriers like fences. Future work is proposed to evaluate the complete integration of the collaborative process into a larger automation framework, incorporating enhanced machine vision applications, quality assurance measures, security features, and considerations for ergonomic adaptability and social human-robot interaction (HRI).

2.5.4. Case study Four

Lin et al. (2020) addresses the challenge of accurately classifying the colours of wooden boards, crucial for enhancing the appearance of wooden furniture created from multiple boards. To reduce computational complexity, researchers suggested a method of colour classification based on machine vision, which involves preprocessing images to eliminate irrelevant colours. They also implemented a K-means algorithm to classify new wood images. The aim is to provide an efficient and accurate mechanism for colour classification in the context of wooden boards.

The study designs a machine vision testbed, incorporating a conveyor, line scan industrial camera, computer, and printer, to capture images of wooden boards. Image preprocessing, feature extraction, offline clustering, and online classification constitute the proposed mechanism. The preprocessing algorithm subtracts background and stains, while the K-means algorithm facilitates offline clustering. An improved algorithm, incorporating centroid improvement and image filtering, addresses abnormal images. As a result, a comprehensive mechanism is developed and demonstrated through experiments to effectively classify wooden board colours.

The paper concludes that machine vision and clustering offer a viable solution in scenarios where human vision struggles due to colour similarity. In this study, the preprocessing algorithm played a key role in removing background stains and stressed the importance of clustering-based mechanisms in handling colour similarity challenges. Future work is proposed to further enhance classification accuracy by exploring new clustering algorithms, such as the G-means algorithm. The study acknowledges the potential for continuous improvement and optimization in the colour classification system for wooden boards.

Chapter 3

3. Methodology

In developing the methodology for this research, the primary focus was to develop a systematic method for investigating the capabilities of collaborative robots focusing on tasks that integrate human-robot interaction and vision systems in real-world applications such as making coffee. This method is intended to answer the research questions initially posed in Section 1.1.

In this context, this research is based on the six layers of the Research Onion (see Figure 3.1) developed by Saunders et al. (2007). Basically, Saunders describes the different decisions that need to be taken when developing a research methodology. By adopting this layered framework, the research ensures a systematic and interconnected exploration of collaborative robot capabilities. Moreover, this framework is a metaphorical tool that helps researchers understand the complexity and interrelated nature of various elements in the research process.

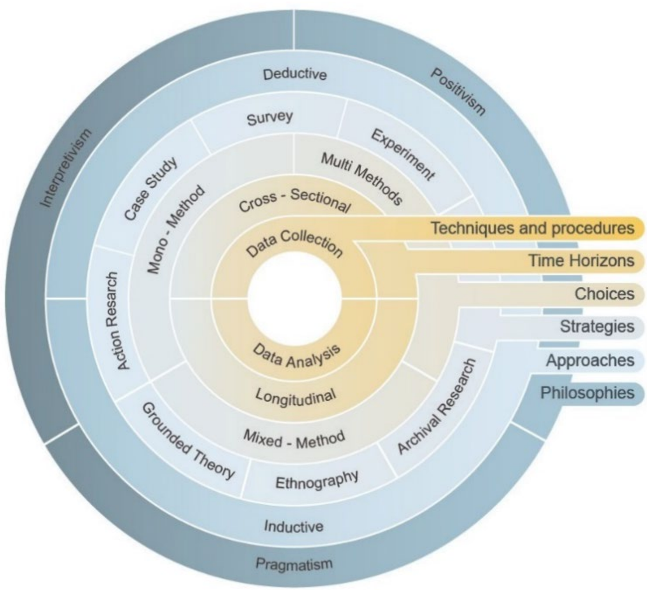


Figure 3.1 The 'research Onion' (Saunders et al., 2023)

3.1. Research Philosophy

The research philosophy meaning can be understood by different ways. According to Mkansi & Acheampong (2012), research philosophy refers to the set of beliefs, principles, and assumptions underlying the research process. It reflects the researcher's worldview and influences their approach to collecting, interpreting, and understanding data. In addition, research philosophy can be described from both ontological and epistemological perspectives. Ontology deals with the nature of reality and what exists (Saunders et al., 2023), while Epistemology relates to the nature of knowledge and how it is acquired (Guba, 1990). Despite Sanders proposed five research philosophies, just three are studied in the context of this research. These are described as follows:

- **Positivism:** Positivism is based on the belief that knowledge can be gained through observable and measurable phenomena. According to Saunders et al. (2023), positivist researchers develop hypotheses using existing theories and thus they commonly use quantitative data. However, they can sometimes change their beliefs. In other words, researchers occasionally have to start from scratch (Park et al., 2020).
- **Interpretivism:** This thinking asserts that social phenomena are too complex to be reduced to quantitative measures alone. It emphasizes understanding the meanings and interpretations people give to their experiences (Alharahsheh & Pius, 2020). Interpretivist researchers often use qualitative methods, such as interviews, observations, and document analysis, to explore the subjective aspects of a phenomena (Saunders et al., 2023).

- **Pragmatism:** Acknowledges the value of both positivist and interpretivist approaches, advocating for flexibility in choosing research methods based on the research question and context (Kelemen & Rumens, 2012). Pragmatist researchers focus on what works best to answer specific research questions, regardless of whether the methods are quantitative or qualitative (Saunders et al., 2023).

Having checked the research philosophies, the pragmatism approach is considered in this thesis, recognising the need to combine positivist and interpretivist elements to comprehensively explore collaborative robot capabilities. Pragmatism allows for flexibility in selecting methods that best serve the research questions. In adopting a pragmatic research philosophy, the primary focus of this study lies in delivering practical and workable solutions. The emphasis is on real-world applications and outcomes, aligning with the pragmatic belief that the success of a research endeavour is measured by its tangible impact.

3.2. Research Approach

According to Saunders et al. (2023), research approach refers to the method by which research questions are formulated, how the study is designed, and how the results are interpreted. In other words, it describes how the research problem or question can be addressed conceptually. It is important to take into consideration the nature of the study, the researcher's philosophical stance, and the research goals as mentioned by Mantere & Ketokivi (2013).The following table summarizes three research approaches in this layer: deductive, inductive, and abductive.

Table 3.1 Research Approach methods (Saunders et al., 2023)

	Deductive	Inductive	Abductive
Nature of Inference	Involves starting with a general theory and applying it to a specific case or set of observations to draw a logical conclusion	Implies generalizing based on specific observations or evidence	Forms the best possible explanation for observations
Logic	Generalising from the general to the specific	Generalising from the specific to the general	Generalising from the interactions between the specific and the general
Philosophical foundation	Positivism Pragmatism	Interpretivism Pragmatism	Pragmatism
Research method	Common in quantitative research.	Common in qualitative research.	Often used in situations with incomplete information
Purpose	Confirming or refuting theories.	Identifying patterns and generalizations	Providing the best explanation given available evidence.

This research employs a hybrid approach, combining elements of both deductive and inductive reasoning. However, as communicated by Suddaby (2006), this incorporation results in an abductive approach. Unlike the linear progression from theory to data in deduction or from data to theory in induction, the abductive approach navigates dynamically between data and theory (Saunders et al., 2023).

3.3. Research Strategy

Saunders et al. (2023) refers to research strategy as the plan or approach that a researcher adopts to address their research questions or objectives. It outlines the systematic steps, methods, and procedures that will be employed to collect, analyse, and interpret data in order to answer the research questions or test hypotheses . Common research strategies include experimental designs, surveys, case studies, content analysis, systematic literature review, ethnography, and more. In this study, a mixed-methods research strategy will be employed to comprehensively explore the capabilities of collaborative robots in human-robot interaction scenarios. The next Figure illustrates how the research strategy is implemented.

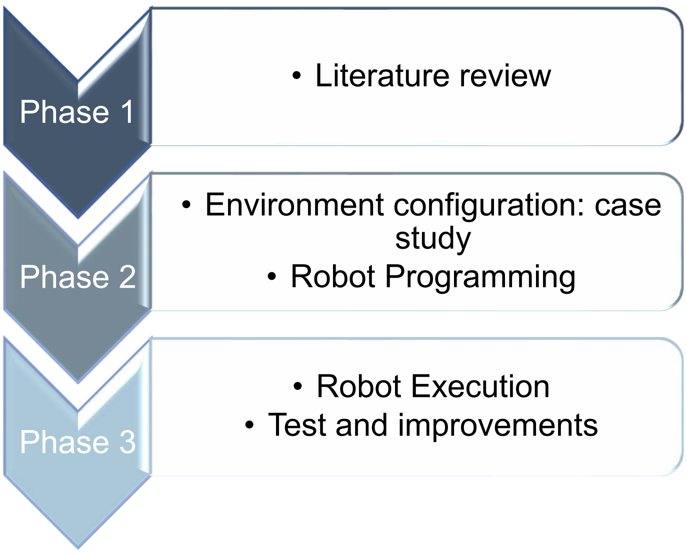


Figure 3.2 Research Strategy

The first phase of research consisted of initially analysing the literature, concepts, technical documentation, and relevant research to identify qualitative data and understand the state of the art in collaborative robotics, integrated vision systems and their applications in service industries. The literature review provided crucial information on industry best practices, security standards, and technological advancements. Furthermore, it reported the development of a conceptual framework that guided the practical implementation of the collaborative robotic system.

Once the theoretical foundation was established, the methodology advanced to phase 2, which has two stages. The first stage is the environment configuration, in which a prior thesis is used as a case study. Then, the programming stage is started. In this phase, the cobot is instructed to carry out the activities, tasks and required behaviour. The joint execution of both stages was essential to guarantee an effective and coherent implementation of the acquired knowledge. A study by Fogli et al. (2022) emphasises the importance of looking at six different knowledge sources when analysing the complexity of programming collaborative robots:

1. **Environment:** Consider where the robot will operate, entities around, constraints, and guiding principles.
2. **Task:** Understand the specific task, including goals and constraint.
3. **User Information**: Know the abilities, limitations, and preferences of the user.
4. **Robot Capabilities:** Explore what the robot can do, its limits, and conditions for safe operation.
5. **Collaboration Design**: Understand how to design effective and safe collaboration between the user and robot, including task-sharing.
6. **Programming Principles**: Be familiar with the principles of robot programming and the specific programming language used.

In the third phase, the focus shifts from theoretical groundwork and programming to the practical execution and application of the collaborative robotic system. This phase is integral for validating the theoretical concepts and ensuring that the developed framework aligns with real-world scenarios. The third phase can be broken down into several key components:

1. **Calibration procedure:**
    - The calibration process is the most fundamental step when deploying a collaborative robot system. Generally, collaborative robots are calibrated according to a calibration scale and the correct axis position. Correct axis position refers to aligning and locating every joint of the robot accurately.
2. **Execution of Programmed Tasks:**
    - A collaborative robot with integrated vision systems is deployed to complete the programmed tasks. This involves the physical implementation of the instructions given during the programming stage.
3. **Testing and Validation:**
    - Thorough testing procedures are conducted to validate the functionality, efficiency, and safety of the collaborative robotic system. This includes assessing the robot's ability to interact with its environment, accurately identify objects using integrated vision, and execute tasks as intended.
4. **Task Implementation:**
    - The collaborative robot is tasked with performing specific actions relevant to the identified applications in service industries. This could involve tasks such as object manipulation, navigation, and interaction with human counterparts.
5. **Real-world Application Scenarios:**

- The collaborative robotic system is evaluated in real-world application scenarios to assess its adaptability and performance within the intended service industries. This phase aims to bridge the gap between theoretical concepts and practical usability.

6. **Iterative Refinement:**

   - Continuous refinement and optimization are conducted based on feedback from the execution and testing phases. This iterative process ensures that any identified issues or improvements are addressed to enhance the overall functionality of the collaborative robot.

3.4. Research Choice

Saunders et al. (2023) refers the term ‘research choice’ as the decision made by a researcher regarding the combination and integration of quantitative and qualitative techniques and procedures in their research design. The research choice entails selecting the specific mix and balance between quantitative and qualitative methods based on the nature of the research questions, the objectives of the study, and the research philosophy. Three different methods are presented in the following figure.

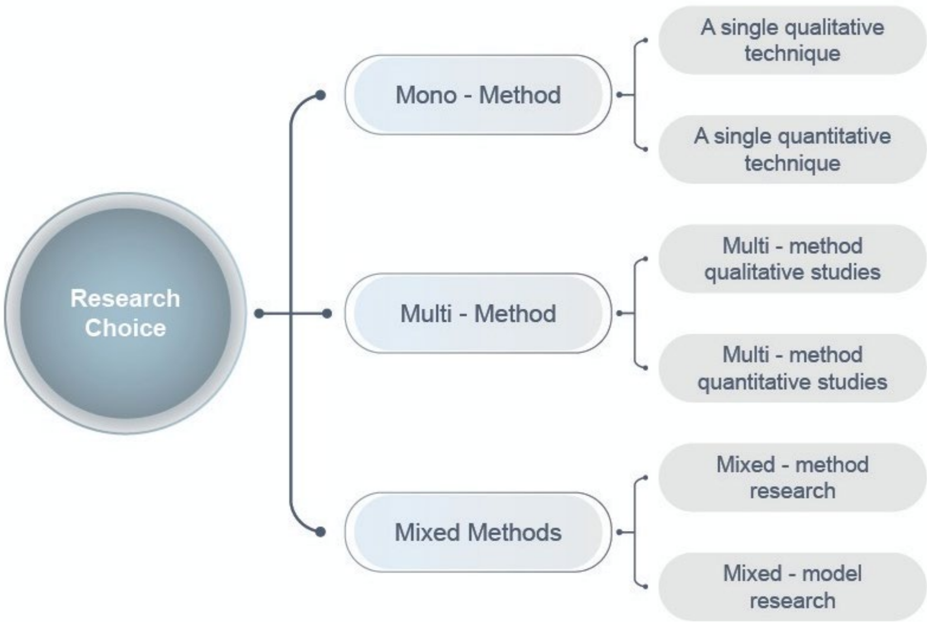


Figure 3.3 Research Choice. (Saunders et al., 2023)

In this thesis, the appropriate procedure is mixed methods. The decision to implement a mixed methods research design is rooted in the complexity and diversity of the research questions proposed in this study. By adopting a mixed methods approach, the research design gains flexibility, allowing for the incorporation of both quantitative metrics and qualitative insights. This flexibility is crucial in holding the various phases of the research strategy, ranging from literature analysis and conceptual development to the execution of practical tasks and real-world application scenarios.

3.5. Time horizons

Time horizons refer to the temporal scope or duration over which a study is conducted (Rindfleisch et al., 2008). This concept helps researchers define the time boundaries within which data will be collected, analysed, and interpreted. There are two types of time horizons: cross-sectional and longitudinal. Cross-sectional time horizons involve collecting data at a single point in time, providing a snapshot view of a phenomenon (Easterby-Smith et al., 2002; Saunders et al., 2023). This approach is effective for gaining insights into the immediate state of variables and relationships within a specific timeframe. In contrast, longitudinal time horizons extend over an extended period, allowing researchers to observe changes and developments over time (Saunders et al., 2023). This approach is particularly valuable for tracking trends, assessing causality, and understanding the evolution of a phenomenon across different points in time. For this research, a cross-sectional approach is employed. While a more extended study would be advantageous for understanding temporal changes, the practical constraints dictate prioritising a concise cross-sectional study.

3.6. Techniques and Procedures

The final layer of the Research Onion focus on detailing the specific methods and processes employed for both data collection and data analysis (Saunders et al., 2023). Jocelyn et al., (2023) conducted their research using an observational approach during their industrial visits to complete the practical observation stage. In the chosen plant, the team meticulously observed eight collaborative applications involving a UR5 cobot associated with a CNC machine for pick and place, alongside a washing station for machined parts. Additionally, a brief observation was made of a UR5 cobot mounted on an autonomous mobile platform. This observational approach aimed to capture the duration of each operation performed by both the cobot and the operator.

In this study, the primary data collection technique is observational, focusing on assessing the collaborative robot's ability to perform the application without errors. This involves systematically observing and documenting the robot's actions during the application of interest. This method is particularly valuable for assessing the real-world performance of the collaborative robot in a controlled environment.

The observational study is conducted by setting up the collaborative robot in a simulated environment that replicates the conditions of the intended application, experiment, or case study. The robot is then programmed to carry out the specified tasks, and its performance is observed without direct intervention. Key metrics and parameters are defined to evaluate the robot's success in executing the application, including accuracy, speed, and error rates. Furthermore, detailed notes are taken during the observation to capture contextual information, any deviations from expected behaviour, and potential errors or challenges encountered.

The collected observational data are systematically analysed to assess the collaborative robot's proficiency in completing the designated tasks. This analysis involves quantitative measures, such as success rates and time taken for each step, providing a quantitative evaluation of the robot's performance. Additionally, qualitative observations and notes contribute to a more nuanced understanding of the robot's behaviour and any potential areas for improvement.

3.7. The chosen Methodology

This chapter provides a comprehensive overview of the selected methodological approach employed in this thesis. Inspired by the Research Onion model, the methodology covers a variety of layers: the philosophical stance, the research approach, research strategy, research choice, the time horizons, the data collection techniques, and the data analysis procedures. An overview of the approaches used can be seen in the following figure.

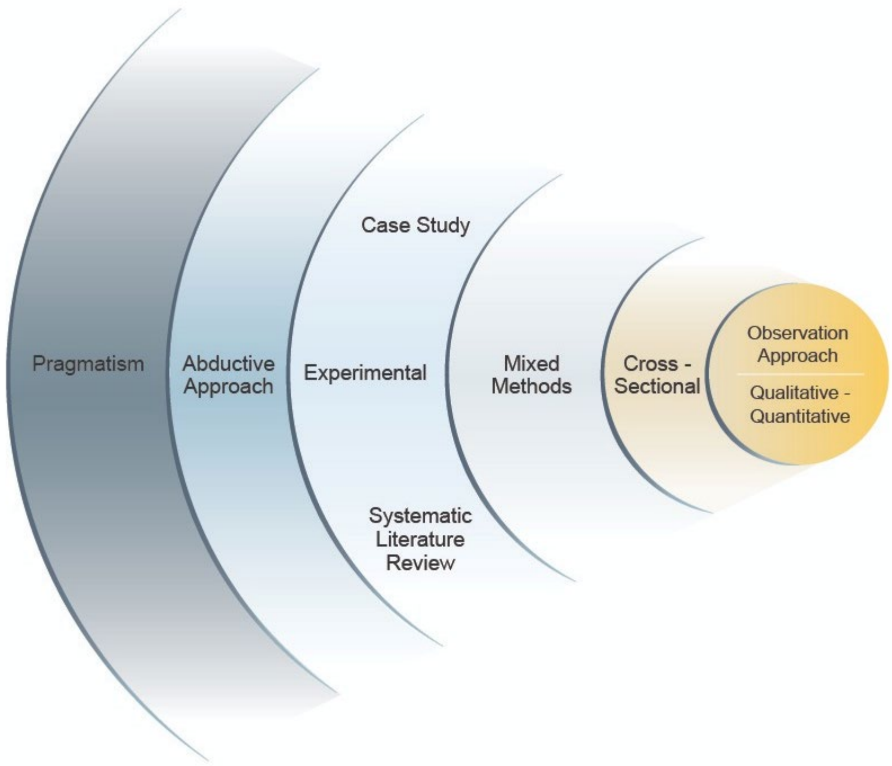


Figure 3.4 Summary of Research Onion methods chosen.

Chapter 4

4. Exploring Collaborative Robot Capabilities in Real-World Applications

This application continues the work of a previous thesis conducted at Sheffield Hallam University Robotics laboratory, using the Dual-arm YuMi-Industrial Robot (IRB) 14000. The earlier study, led by (Aibaogun, 2022), focused on the task of making coffee with the Yumi robot. In this iteration, the exploration of collaborative robot functionalities is extended by adding a new element—integrated vision systems. While the previous study emphasised the robot's physical interactions, the current focus shifts to using the robot's gripper camera for recognising and interacting with coffee pods. This complement study highlights the versatility of the ABB Yumi and expands the range of collaborative robot applications by incorporating advanced vision-based features.

4.1. Dual arm YuMi-IRB 14000: An Overview

The YuMi-IRB 14000 (see Figure 4.1) is a dual-arm industrial robot with integrated controller designed by the company ABB. Each arm is meticulously engineered to mimic the dexterity and flexibility of the human arm, providing a remarkable range of motion and precision. Each arm has seven axes or seven degrees of Freedom (DoF) and includes a smart gripper for handling and assembly. The gripper is equipped with one basic servo module and two optional functional modules, vacuum, and vision. Abb provides a pair of getting-started fingers for testing and demonstration purposes, but they recommend changing these fingers according to the actual application (ABB, n.d.). The table below provides general technical specifications of the YuMi robot.

Table 4.1 Yumi IRB 14000 General Specifications. (ABB, n.d.)

Features	**Description**
Total DoF per arm	7
Protection	IP30
Handling capacity per arm (kg)	0.5
Reach per arm (m)	0.559
Total Robot Weight(kg)	38
Max Tool Centre Point (TCP) velocity $({}^{m}/_{s})$	1.5
Max TCP acceleration $({}^{m}/_{s^2})$	11
Pose repeatability (mm)	0.02
Pose accuracy (mm)	0.02
Linear path repeatability (mm)	0.10
Linear path accuracy (mm)	1.36
Communication Interface	100/10 Base-TX Ethernet

Figure 4.1 YuMi-IRB 14000 provided by Sheffield Hallam University.

The ABB Yumi collaborative robot typically uses the IRC5 controller. It provides the computational power and control logic necessary for the operation of the robot, managing tasks such as motion control, communication, and interfacing with external devices (ABB, n.d.).

4.2. ABB's RAPID language

RAPID is the dedicated programming language for ABB robots. A Rapid program is structured into modules, each comprising various routines such as procedures, functions or traps. These modules are classified into two types: program and system (Figure 4.2). The system module encompasses code associated with the installation of the robot, including surrounding equipment, calibration tools, feeders, and service routines. On the other hand, the program module contains RAPID code specific to a particular process or the parts being manipulated by robots. An entry global procedure called Main is located in one of the modules. When the program is executed, the Main procedure is executed. The program modules dedicated to a specific task collectively form a RAPID program, which is treated as a cohesive unit. In this thesis, a RAPID program was created for each arm, resulting in a total of two RAPID programs.

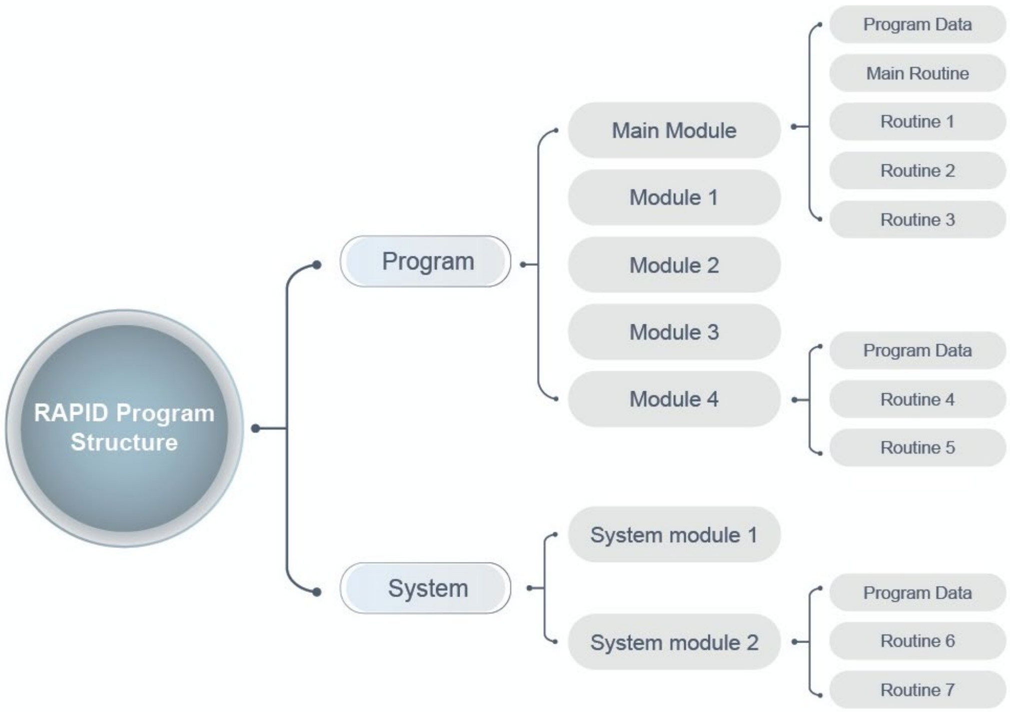


Figure 4.2 Rapid Program Structure

4.3. FlexPendant

Yumi collaborative robot uses the FlexPendant for programming and controlling its actions. The FlexPendant is a handheld device equipped with a graphical user interface that allows users to interact with and program the robot. It serves as a user-friendly control interface for guiding the robot through its tasks, running/edit programs, jogging the manipulator, adjusting parameters, and monitoring its performance in real-time. There are both hardware and software components in the FlexPendant, making it a complete computer on its own. An integrated cable and connector are used to connect it to the robot controller. The Figure bellow shows the main parts of the FlexPendant.

Figure 4.3 Main parts of FlexPendant

4.4. RobotStudio

To complement the hardware and FlexPendant, ABB provides RobotStudio, a comprehensive simulation and programming environment. This software allows users to simulate and validate robotic applications before deployment, optimizing programming efficiency and minimizing the risk of errors. Robot Studio serves as a virtual workspace where users can refine and test their applications in a controlled environment, without interrupting the production system.

The programming environment in RobotStudio enables both online and offline programming of robot controllers. The online mode connects to the actual robot controller, while the offline mode connects to a virtual controller on the PC, simulating the behaviour of the actual robot controller.

4.5. Integrated Vision

Over time, industries have seen significant changes, necessitating the need for more advanced robots that are equipped with innovative capabilities, such as integrated vision systems. To enhance the capabilities and functionalities of industrial robots for collaborative work, ABB has incorporated vision systems into its offerings. The primary goal of these systems is to provide a robust and user-friendly vision solution. The integrated system comprises both software and hardware components that are compatible with the ABB robot controller and the RobotStudio programming environment. Powered by the Cognex In-Sight smart camera family, the vision system employs embedded image processing and an Ethernet communication interface. RobotStudio is also equipped with the same programming environment found in Cognex cameras, namely EasyBuilder. This feature includes tools for 2D part location, part inspection, and identification.

The ABB YuMi IRB 14000 incorporates a Cognex AE3 camera on its gripper as can be seen in Figure 4.3. The camera specifications are described in the following table.

Table 4.2 Cognex AE3 camera specifications (ABB, n.d.)

Feature	Description
Resolution	1.3 Megapixel
Lens	6.2 mm f/5
Illumination	Integrated LED with programmable intensity
Software engine	Cognex In-sight
Programming environment	ABB Integrated vision

Figure 4.4 ABB YuMi camera.

4.6. Application Setup

As a first step, familiarity with the ABB YuMi 140000 collaborative robot was achieved. This involved understanding the software and hardware with which the robot works. In addition, simulations (see Figure 4.2) were carried out on Robot Studio to understand the robot's motion, coordinate systems, and validate and programming modes of the robot.

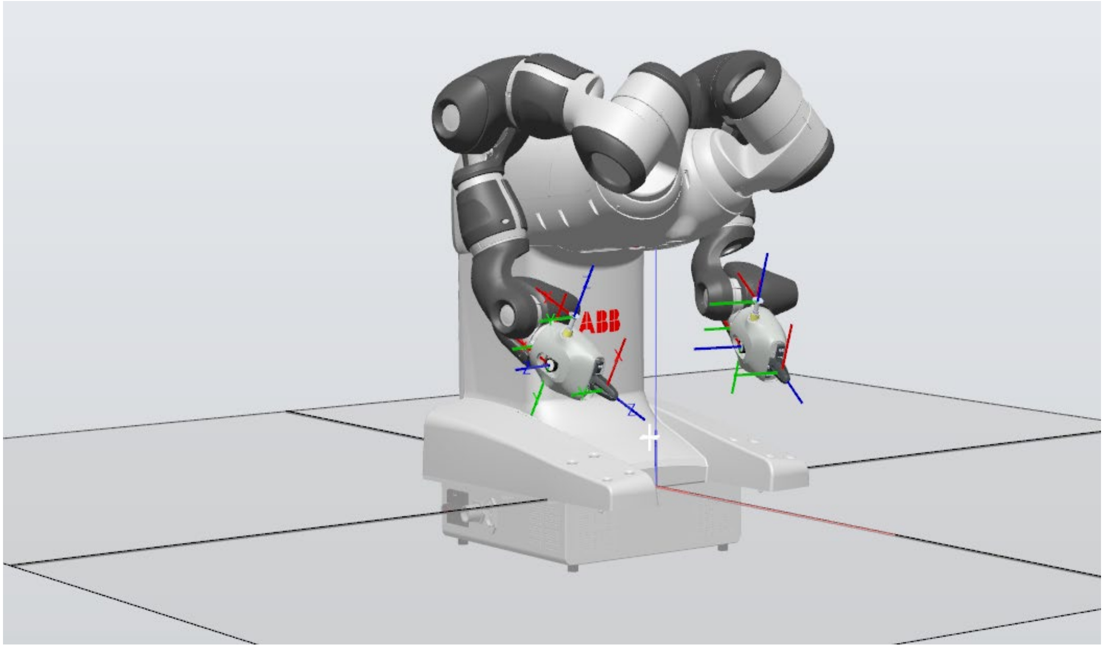


Figure 4.5 IRB YuMi 14000 simulated in Robot Studio.

Before start programming in the real robot, it is important to define tools, payloads, and robot's work environment. The tools and payloads can be edited or updated but is recommendable to define the basic tools in advance. These definitions are explained in the following subsections.

4.6.1. Design of workstation and tools

Once the functionalities of the robot were understood, the robot's work environment was configured. This setup consists of a worktable designed by the prior researcher. The preceding researcher also created 3D components like coffee cups, saucers, and mounts for demonstration applications. However, in this thesis, new holders for plates, cups, and coffee pods were developed. All these components were modelled in 3D using SolidWorks software. After ensuring that all measurements were correct, they underwent laser cutting. The figure below illustrates one of the design processes for the coffee pods holder.

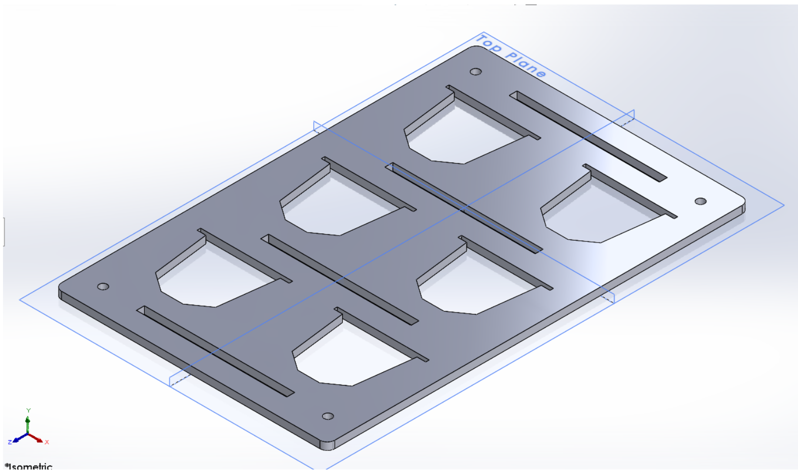


Figure 4.6 Coffee pods holder

Aibaogun (2022) encountered a problem with his application while performing the cup-grabbing process. The fingers that come by default with the robot are unsuitable for grasping these objects. Then, he proceeded to design new fingers for the robot. In this thesis, the same fingers were used for the new application. Figure 4.5 shows the new fingers of the Smart gripper on the right arm. In the Smart gripper on the left arm, the Getting-started fingers are maintained but Plastazote foam is added to enhance the frictional contact point area (see Figure 4.6).

Figure 4.7 New Fingers for cup-grabbing.

Figure 4.8 Modified Getting-started Fingers.

The following Figure shows the complete collaborative workspace after having developed all the objects and made the corresponding improvements.

Figure 4.9 Robot Collaborative Workspace

4.6.2. *Robot Calibration process*

During this stage, the robot underwent configurations and calibrations. The robot can execute two types of calibrations: updating the revolution counters and fine calibration. Fine calibration becomes necessary when components of the robot, such as motors or transmission parts, are replaced. Updating the counters calibration is conducted when the controller is initiated for the first time. However, the manufacturer recommends this last calibration in the following situations:

- The battery is discharged.
- A resolver error occurs.
- The signal between a resolver and measurement board is interrupted.
- A robot axis is manipulated with the control system disconnected.

In this thesis, the calibration of update revolution counters was carried out every time the robot was turned on since the robot's battery was defective and therefore the memory of the revolution counter was lost. The steps of this calibration must be done using the FlexPendant and these steps are shown below.

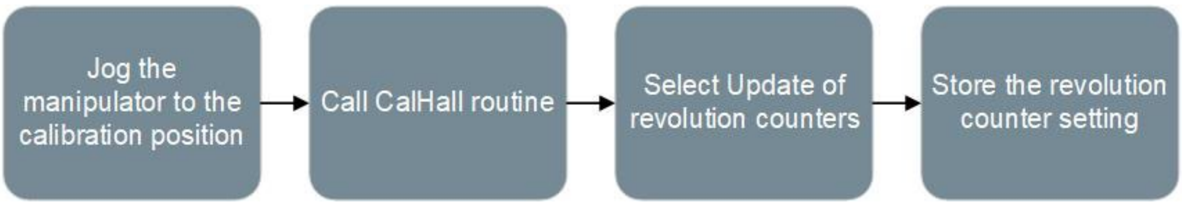


Figure 4.10 Update revolution counters Calibration

The calibration position is also known in this thesis as the home position. Is better to have a home position for the robot when start and finish any process. Figure 4.10 illustrates the positions of the calibration scales and marks on the robot that match the home position. Figure 4.11 shows the robot in its calibration position.

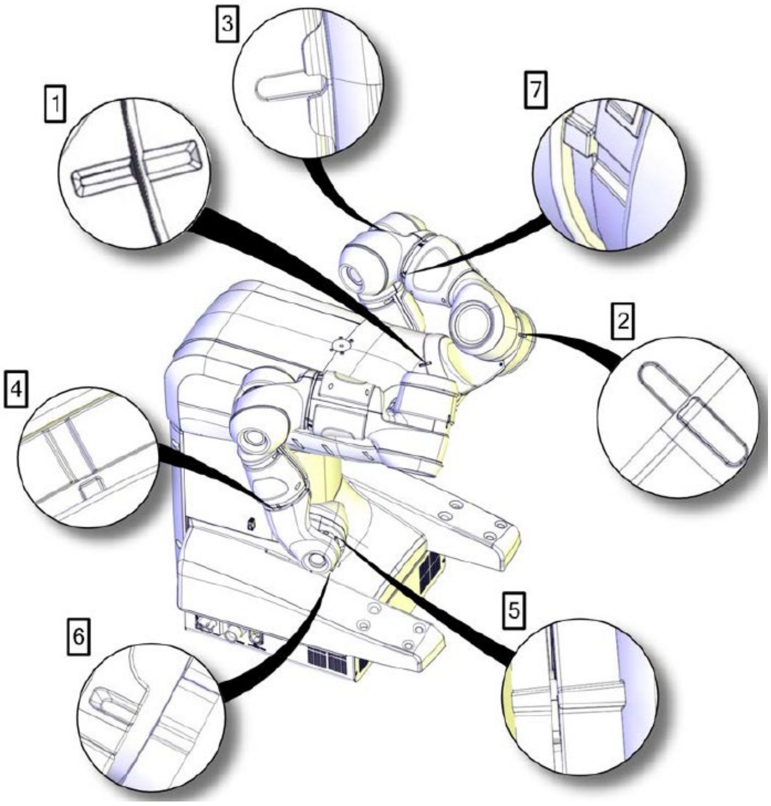


Figure 4.11 Positions of the calibration scales and marks (ABB, n.d.)

Figure 4.12 YuMi in its Calibration/Home position (ABB, n.d.)

Once the process has been completed, it should be ensured that the calibration was successful. To achieve this, the verification can be done on the FlexPendant, where the correct position of the axis for each arm is displayed. The accurate values for each arm at the home position in degrees are presented in the following table.

Table 4.3 Axis home positions in degrees

Axis	Right arm	Left Arm
1	0°	0°
2	-130°	-130°
3	30°	30°
4	0°	0°
5	40°	40°
6	0°	0°
7	-135°	135°

4.6.3. Tool data definition process

The end effector of a robot, often referred to as the robot's "hand" or "tool," is the device or tool attached to the robot's arm that interacts with the environment. It is the part of the robot that performs the specific tasks or operations, such as gripping, welding, cutting, or any other action, depending on the robot's application.

Configuring the end effector of a robot is a crucial step in optimising its overall performance and functionality. This process ensures accuracy and precision in task execution, allowing the robot to perform with the required level of detail. Safety considerations are also embedded in the configuration, preventing accidents, and ensuring both human’s and robot’s well-being.

Before moving the robot arm with jogging or lead-through, the tool data of the mounted gripper or tool must be defined. In this stage, two end effectors were configured, one for each arm. The initial configuration involved setting up the first tool on the left arm by referring to 2.3.1 Technical data, General-Product manual - IRB 14000 gripper (ABB, n.d.). Given that the configuration of the Smart gripper on this robot encompasses servo, vision, and vacuum functionalities, the corresponding values are as follows.

Table 4.4 Technical data for the left arm end effector.

Servo+Vision+Vacuum			
Weight and load capacity of the whole gripper	**Weight (g)**	**Max. load capacity (g)**	
	262	238	
Detailed mass data - Centre of Gravity (CoG) of the whole gripper	CoG (mm)		
	x	y	z
	7.8	11.9	50.7
Detailed mass data – Inertia of the whole gripper	Inertia (kgm^2)		
	Ixx	Iyy	Izz
	0.00022	0.00024	0.00009
Tooldata definitions of the whole gripper	Tooldata		
	[TRUE, [[0, 0, 136], [1, 0, 0 ,0]], [0.262, [7.8, 11.9, 50.7], [1, 0, 0, 0], 0.00022, 0.00024, 0.00009]]		

It is also crucial to specify the length from the robot's mounting flange to the end of the fingers, as that value is configured in the Tooldata information. The next figure illustrates that the value is 136 mm.

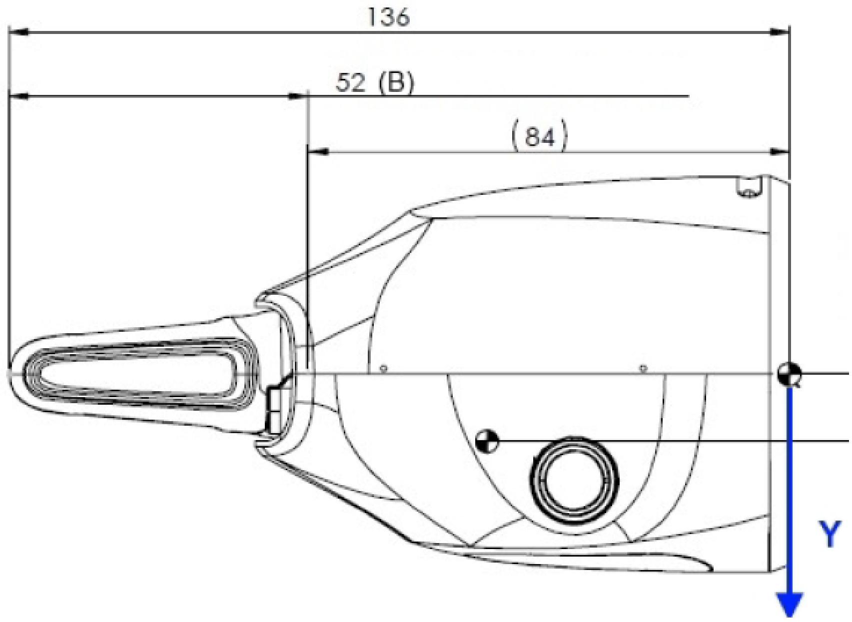


Figure 4.13 Length from the robot's mounting flange to the end of the fingers. (ABB, n.d.)

Hence, the process to configure a new Tooldata and its values (see Table 4.4) on the FlexPendant for the left arm is as follows.

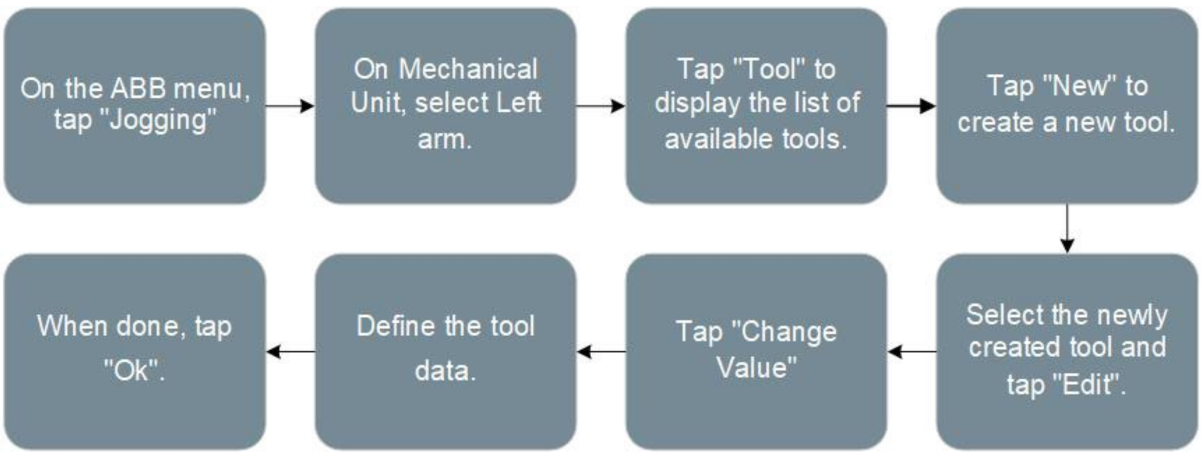


Figure 4.14 Left arm tool Data definition.

The configuration of the end effector of the right arm is slightly different because the getting-started fingers were changed. If customised grippers or payload are mounted, it is recommended to run the service routine “LoadIdentify” from the Program Editor to obtain accurate configuration of tool data. So, the steps to configure the new tool on the right arm is as follows.

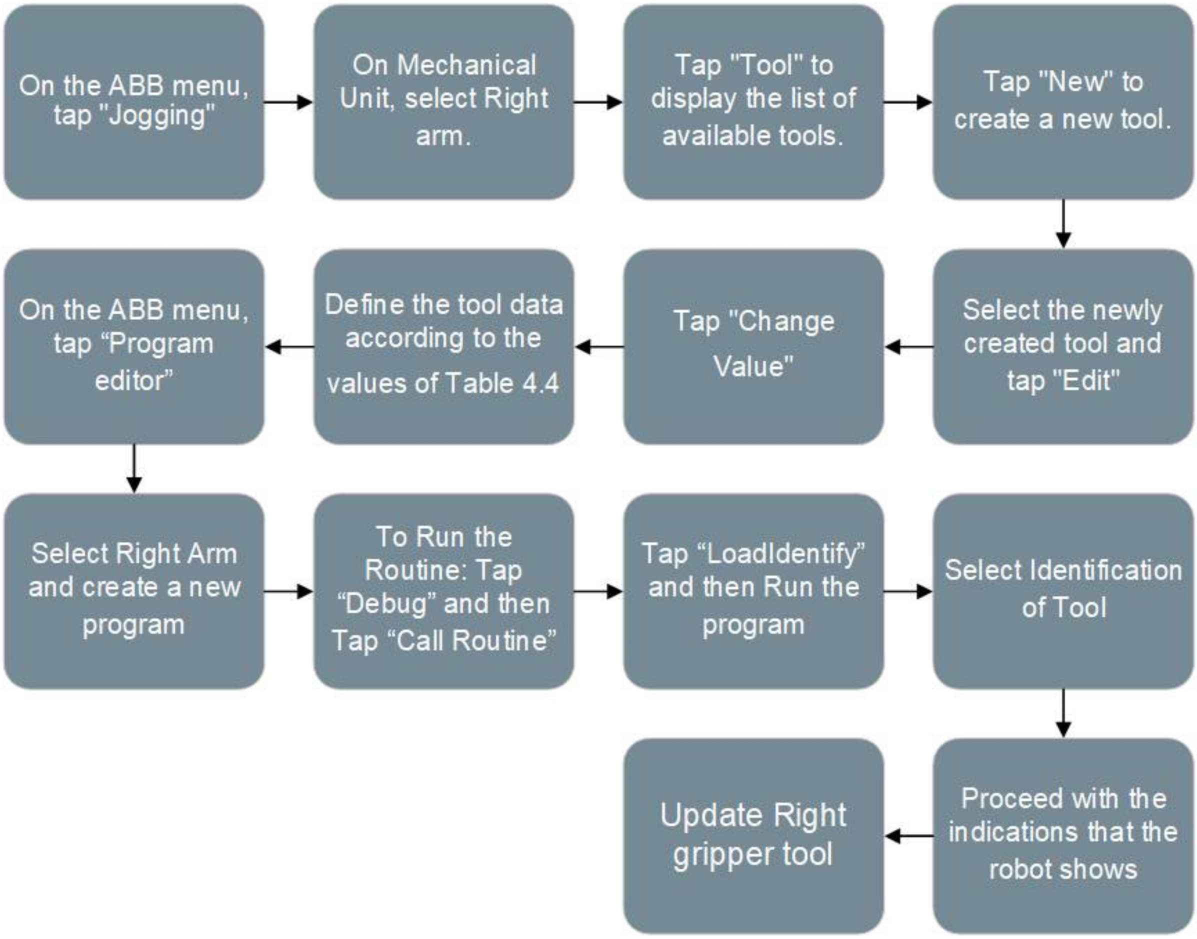


Figure 4.15 Right gripper tool Data definition.

After selecting the Tool identification step, the robot prompts on the FlexPendant screen to jog the right arm to a specific position before initiating the service routine. The arm routine is illustrated in Figure 4.15 and the results obtained for the new gripper are outlined below.

Table 4.5 New Right gripper values

Right Tool Identification			
Mass (Kg)	0.38		
Centre of gravity (mm)	x	y	z
	9.4	-10.1	40.8

Figure 4.16 Tool Identification Routine

4.6.4. Payload definition process

The Payload identification process is critical for the efficient functioning of the robot. By accurately identifying and configuring the payload, a precise understanding of the weight being handled is gained by the robot. This information is crucial for optimizing the robot's movements, ensuring the safety of both the robot and its surroundings. The accurate payload data enables the robot to determine the appropriate force and speed required for tasks involving lifting and manipulation, contributing to enhanced performance, efficiency, and overall reliability in its designated applications.

In this application, the right gripper was used to lift the cups and the left gripper was used to lift the saucers and coffee pods. Is the same process for each gripper to identify the payload of an object and it is outlined below.

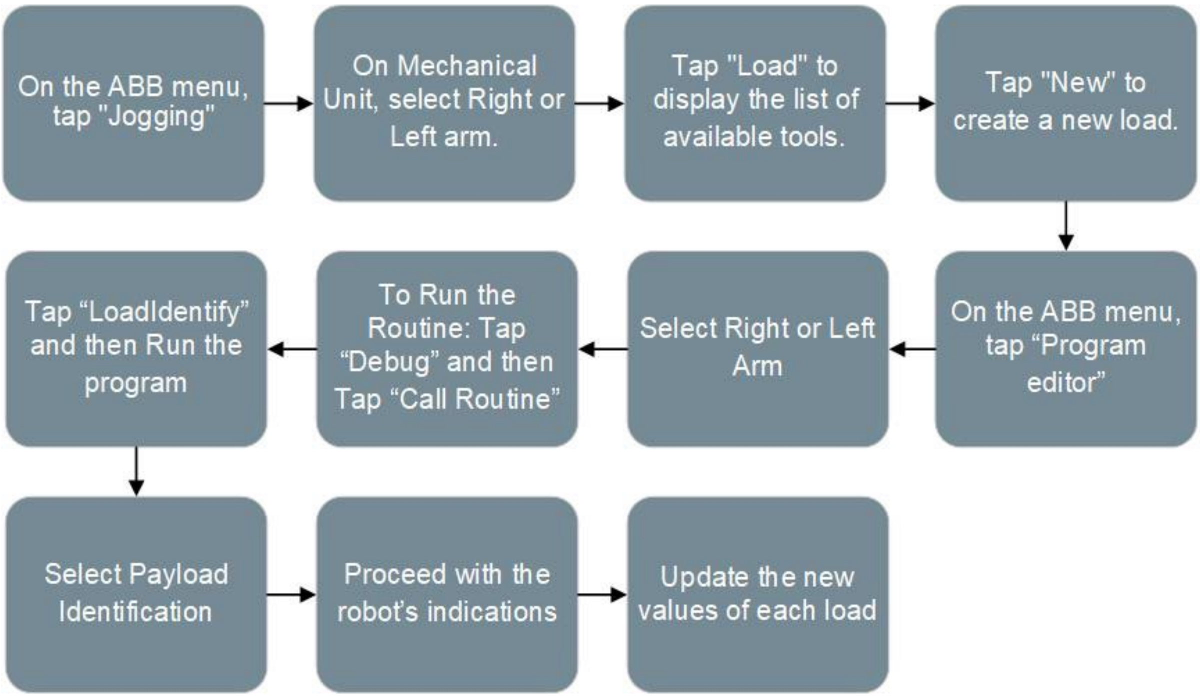


Figure 4.17 Payload Identification routine

After selecting the Payload identification step, the robot prompts on the FlexPendant screen to jog the right or left arm to a specific position before initiating the service routine. The left arm routine is illustrated in Figure 4.17 and the right arm routine is illustrated in Figure 4.18. The results obtained for the cup and saucer payload are outlined below.

Table 4.6 Saucer and Cup Payload values

	Saucer			**Cup**		
Mass (Kg)	0.21			0.14		
Centre of gravity (mm)	x	y	z	x	y	z
	7.4	-27	-37.1	-3.1	-9.8	15.6

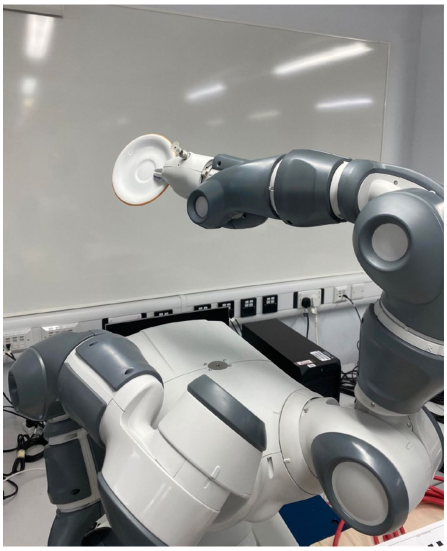


Figure 4.18 Saucer Payload Identification routine.

Figure 4.19 Cup Payload Identification routine

4.7. Programming the ABB YuMi IRB 14000

In this research, both the FlexPendant and RobotStudio were used for programming. The FlexPendant was used for modifying programs, such as trajectories, positions, and picking-place tasks, while RobotStudio was used for more complex programming. RAPID code of the controller is structured into modules.

First of all, the FlexPendant was used for both jogging and lead-through functions to manipulate the robot's axes. This allowed to save the trajectories and positions into the RAPID programs. Jogging entails the manual positioning or movement of robots or external axes using a joystick, adhering to the configured coordinate system. This project utilised the robot's base coordinate system and the work object coordinate system. The base coordinate system, with its zero point at the base of the robot, was employed when moving the axes between points. Conversely, the work object coordinate system corresponded to the workpiece, particularly when positioning the end effector above the objects for interaction.

On the other hand, lead-through function on the YuMi robot played a crucial role, allowing the robot to physically move through the desired motions, capturing and storing key positions for later use. All changes were saved and upgraded while the application was progressing. The subsequent RAPID commands were executed to pick-place the cups, saucers, and coffee pods to the desired positions:

Table 4.7 Rapid commands used to perform the coffee-making task.

Command	Description
MoveJ	Move the robot and external axes to the destination position along a non-linear path.
MoveL	Move the tool centre point (TCP) linearly to a given destination.
WaitRob	Wait until the robot and external axes have reached stop point or have zero speed
WaitTime	Wait a given amount of time.
WaitSyncTask	Synchronise several program tasks at a special point in each program.
Offs	Add an offset in the object coordinate system to a robot position.
GOTO	Transfer program execution to another line within the same routine.
g_MoveTo	Move the gripper to a specified position.
g_GripIn	Indicate the gripper to grip inward
g_GripOut	Indicate the gripper to grip outward
g_Calibrate	Calibrate the gripper in a particular position. Only after the gripper is calibrated, it can be instructed to perform movement or gripping.

The RAPID editor tab in RobotStudio serves as a platform for creating, editing, and managing RAPID programs, with a focus on tasks other than robot motion. Adopting an object-oriented programming paradigm within the RAPID language proved beneficial for improving code organization and maintainability. In this approach, each task of the application was encoded in routines, and these routines were subsequently called in the main routine. This approach facilitated the systematic arrangement of code components, contributing to a more modular and scalable program structure. The following table provides a description of the application process, outlining the specific actions performed by each arm.

Table 4.8 Application Process for each robot arm

Sequence	Right Arm	Left Arm
1	Grab the cup	Open the coffee machine lid
2	Place the cup under the coffee machine spout	
3		Grab the saucer
4		Place the saucer on the mount
5		Image acquisition
6		Grab the selected coffee pod
7		Place the coffee pod in the coffee machine
8		Close the coffee machine lid
9	Wait for the coffee to be ready	Wait for the coffee to be ready
10	Place the cup on the saucer	Wait Time
11	Return to the Home Position	Return to the Home Position

To achieve the sequence five, programming and configuring the vision task are essential steps. As part of the RobotStudio package, an additional tab is provided that can be launched when the software is connected to a robot controller with the option Integrated Vision. With the help of a graphical interface, users can quickly and easily assemble a vision task or job using point-and-click instructions. In the vision tab, several vision tools can be used to address a variety of applications. One crucial process involves saving distinctive features and figures of six coffee pods. Consequently, when a customer specifies their coffee preferences, the robot executes a snapshot process, capturing the visual characteristics of the coffee pod. The RAPID program then initiates a comparison, matching the current features with those saved in the vision system program. This dynamic process enables the robot to adapt its actions according to the customer's choices. The following Figure shows the steps that were used to create the vision application.

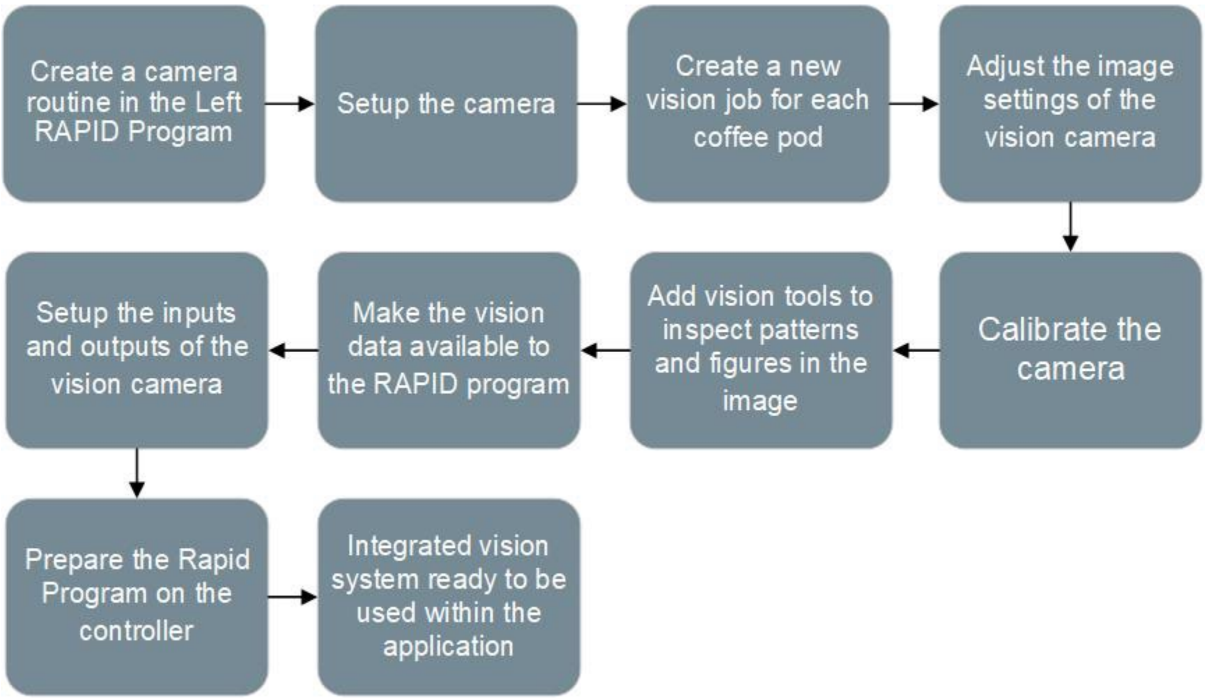


Figure 4.20 Vision programming procedure

4.8. Application Summary

In summary, the application process involves the utilization of ABB's collaborative robot, YuMi, in conjunction with an integrated vision system for coffee preparation. The process begins with configuring the robot's environment, including setting up the workspace and designing 3D-printed components for cups, saucers, and coffee pods. The calibration stage ensures accurate movement and positioning of the robot's arms, followed by payload identification crucial for lifting cups and plates. The end effector, a Smart gripper, is configured for precise interactions. The Integrated Vision system, based on Cognex In-Sight smart cameras, is calibrated, and programmed to recognise the visual features of coffee pods. The application programming, executed in the FlexPendant and RobotStudio using RAPID language, employs object-oriented programming for modular and scalable code. The vision system dynamically adapts to customer preferences, allowing the robot to perform tasks such as recognising objects, picking-placing items, ultimately showcasing the collaborative capabilities of YuMi in a real-world application. The details of the developed system are illustrated in the following figure.

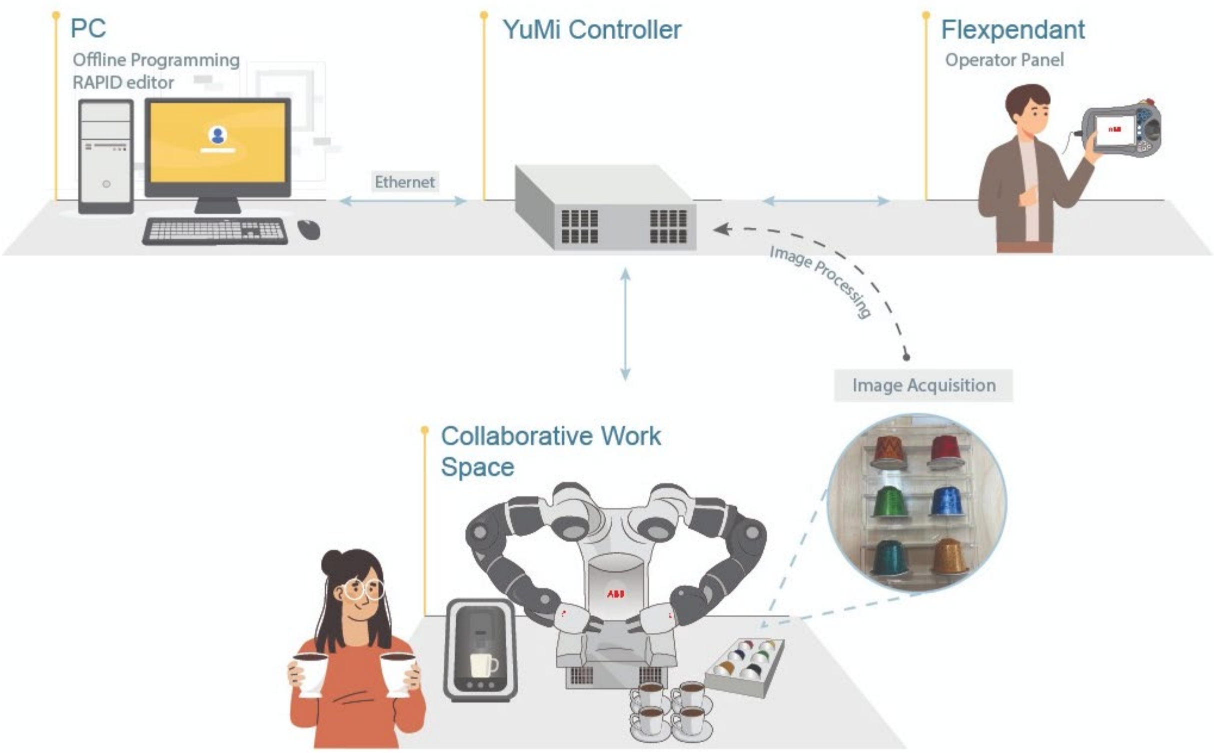


Figure 4.21 System Overview for making-coffee and human-robot interaction

Chapter 5

5. Results & Discussion

The experimental phase of this study sought to assess the performance and capabilities of the cobot within the established application framework. By conducting a series of 20 tests, a comprehensive evaluation was undertaken to determine the system's reliability and identify areas for improvement. The chosen approach adheres to the pragmatic research philosophy, emphasizing a blend of quantitative and qualitative methodologies to derive an understanding of the cobots behaviour.

5.1. Observations and Experimental Results

The collaborative robot's performance in diverse tasks was closely inspected. This observational approach involved monitoring the robot's responses, adaptability, and interaction capabilities in real-world scenarios. The method facilitated insights into the robot's behaviour, revealing strengths and areas for improvement. This observational approach, coupled with subsequent analysis, provides a comprehensive evaluation framework, shedding light on the collaborative robot's capabilities and potential enhancements.

In the experimental process, the goal was to quantify the success rates of critical tasks, such as coffee pod selection and saucer handling, to measure the overall efficiency of the robotic system. Of the 20 tests carried out, the following results were obtained.

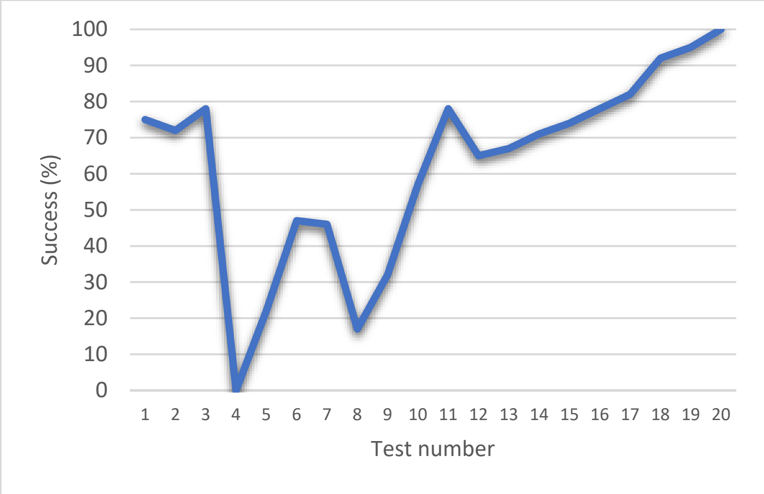


Figure 5.1 Success Rate of Coffee Pod Selection

The system demonstrated an overall average accuracy of 62.4% across the 20 tests. The vision system faced challenges in consistently identifying the correct coffee pod, necessitating corrective actions in the vision programming. Adjustments, including threshold modifications and fine-tuning brightness and contrast, were implemented to address these challenges. Following these corrections, the overall effectiveness significantly improved to 94.3%. It is crucial to emphasize that the lower success percentages did not impact the coffee preparation, with the exception of the test that recorded 0% success, resulting in the incomplete task. The figure below illustrates the success score of one of the coffee pods, which was 98.8%.

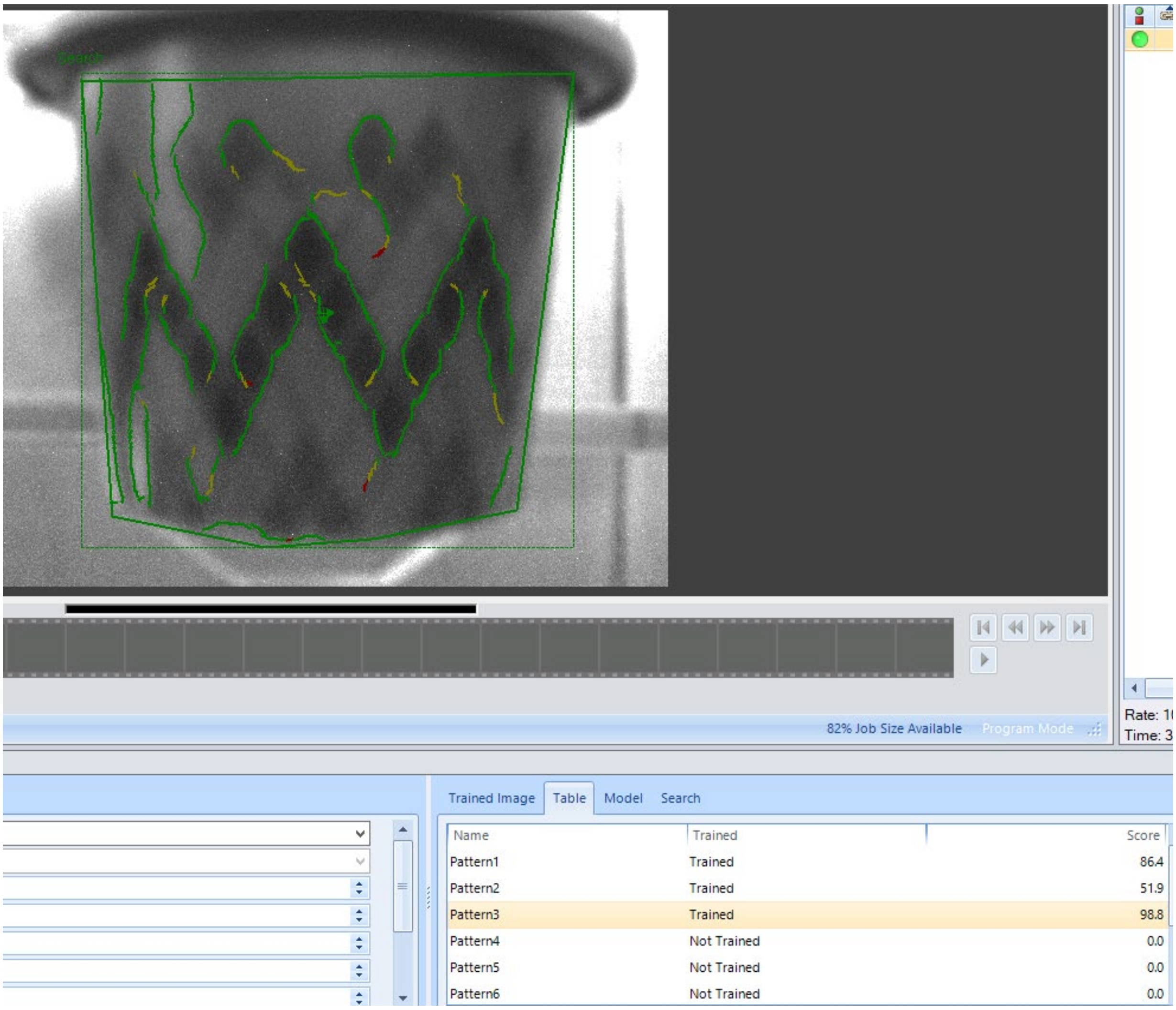


Figure 5.2 Vision test of one of the coffee pods.

The subsequent test focused on the saucer, selected for its weight and challenging grip due to its shape. The results of the Saucer Stability Analysis are presented in the figure below.

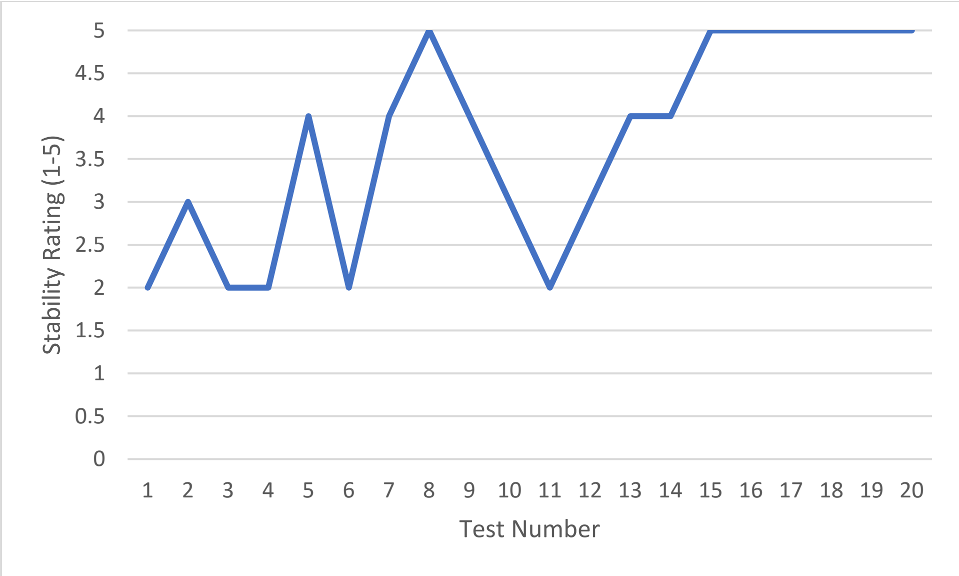


Figure 5.3 Saucer Stability Analysis

The system demonstrated an overall average accuracy of 74% across the 20 tests. This challenge involved addressing saucer instability during the operation. To enhance gripping capabilities, the fingers were upgraded with Plastazote foam, as described in section 4.6.1. Additionally, modifications were made to the arm speed to prevent accidental falls.

5.2. Qualitative Results

In the context of the qualitative assessment of the collaborative robot, it is imperative to highlight two key aspects that have emerged significantly: task completion and human-robot interaction. These elements not only represent fundamental indicators in evaluating the robot's performance but also underscore its ability to successfully integrate into diverse operational environments.

Regarding task Completion, the performance of the collaborative robot in task execution has been successful, standing out for its ability to complete each task with precision and order. Operational analysis revealed that the robot consistently grabbed and placed objects, such as cups, saucers, and coffee pods, accurately, creating synergy between each action. Furthermore, the robot's ability to follow a predefined sequence with precision reflects its effectiveness in addressing operational challenges. Instances of mishandling or falls were minimal and easily resolved, demonstrating that the cobot is a reliable and efficient tool in diverse environments.

On the other hand, throughout test trials and operational cycles of the robot, the dynamics of interaction between humans and the machine were analysed, revealing a highly successful collaboration between the robot and the user. The robot notably demonstrated its ability to adjust its actions according to the individual preferences of the user, resulting in an experience that is not only intuitive but also easy to manage. Additionally, in terms of safety, the robot proved highly reliable when working in proximity to humans, effectively stopping its operations upon detecting the user's presence. This aspect highlights the efficiency of the collaborative robot in interacting with users during the coffee preparation process, solidifying its performance as secure, versatile, and adaptable in collaborative environments.

In summary, the ABB YuMi - IRB 14000 not only meets but exceeds expectations, demonstrating a high level of efficiency, adaptability, and safety. These analyses position the robot as a valuable asset in various applications, particularly in environments where seamless collaboration between humans and machines is paramount. The qualitative results reinforce the robot's standing as a reliable, versatile, and user-centred solution, supporting its successful implementation in precision manufacturing environments and its potential for future research studies and applications.

Chapter 6

6. Conclusions and Future work

This thesis provided a comprehensive examination of the current state of collaborative robots, focusing on their capabilities and practical applications in real-world contexts. Through this analysis, innovative ideas and underexplored approaches were contributed. This effort advanced the field of collaborative robotics, providing new perspectives and potential avenues for further research and development.

A collaborative robotics system was implemented using a case study from a previous thesis. After analysing related work and understanding the application and the gaps that existed in that research, it was possible to not only recreate the application but also integrate a vision system to improve the decision-making capabilities of the robot. As a result, the YuMi collaborative robot was perfectly adapted to this application that simulates a real scenario, providing efficiency and safety to the operational work environment.

Through the study and implementation of the vision system, a substantial improvement in the robot's performance was evident, expanding its capabilities in different types of tasks. The robot showcased swift adaptability to human preferences by effectively analysing and recognizing objects. Consequently, the robot adeptly fulfils its role in the collaborative work cycle without posing any risks to humans.

6.1. Limitations

- The study was confined to the specific capabilities and functionalities of the ABB YuMi robot, limiting the generalizability of findings to other collaborative robotic systems.

- Time-constraints imposed limitations on the depth of exploration into certain aspects of collaborative robotics, such as a more exhaustive examination of the integrated vision system's intricacies.
- The inability to modify certain parameters of the robot and network configurations within the RobotStudio environment restricted the ability to optimize certain elements for the application.
- The grayscale-only image capture capability restricted the scope of the study, preventing a thorough examination of the robot's performance in scenarios where colour recognition is a critical factor, impacting the generalizability of the findings to colour-sensitive applications.

6.2. Future work

- Prospective research could explore the integration of a Programmable Logic Controller (PLC) within the collaborative robot system, enabling communication and coordination with other industrial components. Additionally, incorporating a Human-Machine Interface (HMI) may enhance the user experience and provide a user-friendly interface for monitoring and controlling the collaborative robot's operations in a broader application context.
- Further investigations could focus on refining the machine learning algorithms integrated into the collaborative robot's programming, aiming to optimise its adaptability to dynamic and unstructured environments, thus expanding its practical applications.
- Future research endeavours may explore enhancing the collaborative robot's vision system by incorporating advanced colour imaging capabilities, allowing for a more comprehensive analysis of its object

recognition and decision-making processes. It is also recommended to build a separate machine vision system and use other software to carry out the image processing process.

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