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**Workspace design and monitoring framework to evaluate the
collaboration between human-machine**

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Abstract

Industrial development is marked by a pronounced shift towards human-machine collaboration, a trend exemplified by the beginning of Industry 5.0. This evolving industrial paradigm prioritizes human-centered solutions, emphasizing resilience and sustainability. A vital part of this collaboration is the need for robots to possess more complex cognitive abilities, facilitating safe co-working environments with humans. Technological advances have enabled diverse methods for monitoring human behavior. Analyzing these behavioral patterns enhances efficiency and collaboration.

This study introduces a setting where monitoring the operator and the robot is possible. It is achieved through a camera, an indoor positioning system, and wearable sensors. The collaboration can be represented by indicators (utilization of participants, level of stress based on physiological measurements of the person).

Targeted measurements were conducted, and the results underwent comprehensive analysis. The objective is to bridge the gap between human activities and collaborative robots and design their service to human needs. The developed methodology is presented in a complex demonstration game, and a design of experiments is shown.

Keywords: Collaborative robot, human-robot interaction, indoor positioning system, design of experiments

Chapter 1

Introduction

The manufacturing workforce faces a severe shortage of human labor globally and in Europe, driven by an aging population and rapid technological changes. A WHO report predicts that by 2024, those over 65 will outnumber those under 15 in the WHO European Region. This demographic shift poses challenges in social, economic, and health aspects, impacting the European economy by slowing down growth and reducing competitiveness [1]. Consequently, the need for solutions becomes apparent, and while some automation is possible, establishing a shared space for close interaction between humans and machines is crucial. This is what I am trying to provide a solution for. The industrial sector has become more digitalized, using automation and wireless communication. This trend, known as Industry 4.0, is gaining popularity among researchers. However, digitalization alone cannot solve all problems, and society must consider sustainability, resilience, and human-centered solutions [2]. Industry 5.0 addresses the differences between manufacturing and social needs by focusing on collaboration between humans and robots. This collaboration allows for the co-creation of products and a complementary working environment, as resilience, sustainability, and collaboration are crucial for the future [3].

The interactions between operators and machines have changed with the new industrial revolution [4]. However, even in the so-called smart factories, where there is data sharing between intelligent robots, workers are still seen as spectators, not an active part of the system. To change this and bring human-centered manufacturing to the forefront, robots should not replace the jobs of human workers but work together and assist the workers in helping with efficiency and productivity. The interaction between operators and machines has evolved through the years. The first generation, Operator 1.0, is when the human worker does manual work and is assisted with some support by the machine or uses manually operated tools. The Operator 2.0 generation represents when the operator works assisted by computers (for example, CNC machine tools) and information that links the

system. In the next generation, the worker cooperates with machines and computer tools. Operator 3.0 is what they call a human-robot collaboration (HRC) system. The future is represented by Operator 4.0, whose work is supported by machines when necessary because of their skills. The focus is on a system where automation further enhances human worker abilities [5]. Operator 4.0 aims to create a partnership between workers and machines that involves trust and cooperation. This way, the smart factories can combine the intelligent robots' powers and help their qualified and competent operators with new skills to take full advantage of every opportunity in the created system [6]. The operator can be supported in many forms; depending on that, it improves one of its skills. As a result, workers can be supported in many ways, improving their skills and abilities. As Industry 4.0 enhances the capabilities of manufacturing systems, it should also empower the workforce. The concept of Operator 5.0, particularly the "Resilient Operator 5.0," envisions a skilled individual using creativity and technology to overcome challenges, ensuring sustainable operations and workforce well-being in difficult conditions [7].

The goal is to create a framework where it is possible to monitor and analyze robot-human collaboration. In light of this, I will review the following topics: collaboration, monitoring of the collaboration, cognitive systems, human-machine interaction, and the evaluation of these interactions. With the developed framework and based on the measurements, I will propose a design of experiments.

Following this introduction and the literature review, in Chapter 2 I will present the framework and its components. Chapter 3 shows the developed collaborative workspace at the Operator 4.0 laboratory, where I conducted experiments to analyze the learning curves for pattern building and the micro and macro movements of the human operators, leading to a thorough analysis of results and discussions of the experiments in Chapter 4. The following section, Chapter 5 is dedicated to the design of the experiment, explaining the methodology and parameters employed based on the experiences. The thesis concludes with a synthesis of findings in Chapter 6, outlining potential avenues for further exploration in human-robot interaction.

1.1 Collaboration

A new generation of robots was introduced called collaborative robots - cobots [8]. These industrial robots have been set up to replace human assistants or help in varied repetitive manufacturing tasks that are hazardous and monotonous to the worker. In the case of using collaborative robots, humans and robots are sharing a workspace. Thus, new human-robot interaction systems have been created for such systems to be able to enhance the abilities of both humans and robots [9]. Cobots are designed to work alongside

humans, using advanced safety technologies to ensure the appropriate level of automation. However, the systems become more complex as the collaboration between humans and cobots increases. This complexity has limited the industrial application of cobots in labor-intensive processes such as assembly [10].

Therefore, sets of methods are used to ensure safety during collaboration. Hand-guiding (HG) is used to drive a tool at relatively high speeds manually. It is compatible with human arm movements and generates the robot's trajectory at execution time. Another method is Speed and Separation Monitoring (SSM), which continuously monitors the motion of humans in the workspace and ensures a minimal protective distance to avoid collisions. Finally, the Power and Force Limitation (PFL) method reduces the effects of accidental impacts and maintains any contact under certain limitations [11]. The Safety-Rated Monitored Stop (SRMS) method allows humans and robots to work in different areas. The robot has the autonomy to perform its tasks without limitations as long as the human is not present in its workspace. However, the human can only enter the robot's workspace when a safety-rated monitored stop is active, and the robot can only resume its work once the human has left the workspace. For this, safety-rated devices are necessary to detect the presence of humans and ensure their safety. Recent advancements in AI (Artificial Intelligence) have opened up new opportunities to address manufacturing challenges in ways that were impossible before.

Human-robot collaboration can be classified into levels that depend on how humans and robots work together in their respective spaces (see in Figure 1.1). These levels are closely linked to the way they interact with each other during their work [12]. The first level is when the robot is fully programmed. Most industrial robots are such and are pre-programmed to execute a specific set of repetitive actions for a fixed task. To ensure safety, these robots are usually installed behind fixed security barriers that separate the human workspace from the robot workspace. In this setup, the robot's workspace is only available, and the robot's actions do not require any decision-making. The next level, co-existence, involves robots kept separate from humans by a physical or virtual barrier. These robots can still contribute to shared tasks but do not share the same workspace as humans. In this case, robots can be helpful for tasks that require precise movements or are too dangerous for human workers, such as welding or working with hazardous materials. Following, robots can work as assistance; they are designed to help humans with physical tasks that are difficult or impossible for them to do alone. These robots are typically used in settings where they can help with lifting and moving things. Unlike co-existence, assistive robots do not have an independent task space and are designed to work alongside humans. Cooperation is the next level of human-robot interaction, where robots and humans share the same workspace and resources but sequentially work on separate tasks.

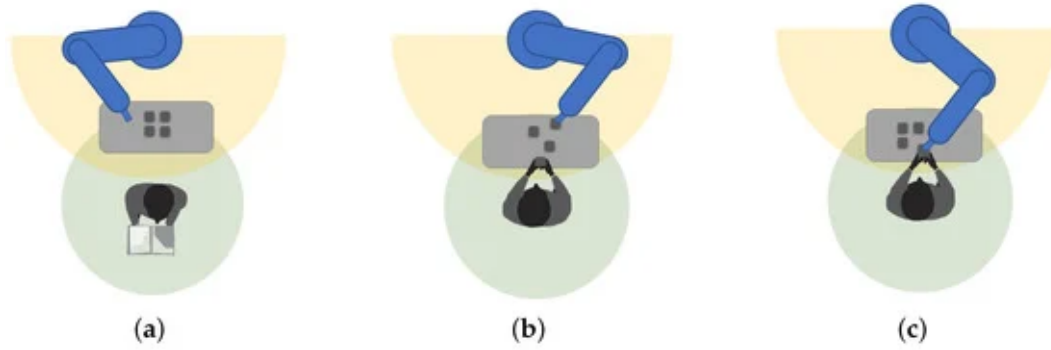


Figure 1.1: Collaboration levels: (a) Coexistence; (b) Cooperation; (c) Collaboration [12]

There is an intervention zone where tasks may be shared, but there is no physical contact between the two. Cooperation robots can be helpful in tasks that require human and robot input, such as assembly lines. The final level is collaboration, where collaborative robots work alongside humans, sharing the same workspace and tasks. These robots can make decisions based on human and robot input and may involve physical contact or communication, such as gestures or voice commands [13]. Collaborative robots are helpful when tasks require close cooperation between humans and robots, such as in advanced manufacturing settings [14]

Additionally, some studies proposed task planning for collaborative work between humans and robots based on human motion prediction. For example, Liu et al. proposed a probabilistic model for human motion prediction for task-level human-robot collaborative assembly [15]. Finally, another example introduced an integrated framework for human-robot collaboration, where the robot perceives and adjusts to human actions [16]. Human motion prediction has been effectively applied to various human-robot interaction problems. The first step involves determining the optimal delivery position using a cost function that considers multiple factors, such as the worker's skeletal data measured by a 3-D vision sensor. This cost function is based on human-robot interaction and is designed to find the most efficient delivery position. The second step is to predict the worker's motion using position data from the vision sensor. This prediction helps the robot plan its actions more effectively, and after each work cycle, the worker's model is updated using stored position data. Finally, in the trajectory planning and control step, the robot calculates the optimal trajectory from its current position to the delivery position. The robot's motion controller ensures that it follows the estimated trajectory, enabling the successful delivery of parts/tools to the worker [17].

1.2 Human-machine interface

These developments in automation require research in human-machine interaction to create a suitable interface for collaboration. Many frameworks make the interaction between humans and machines straightforward and robust. The solutions for the interfaces can be a simple Light Emitting Diode (LED) indicator or a more complicated graphical user interface (GUI); while both can transfer information to the person, their complexity varies [18]. The goal for the operator is to understand the system's current behavior and intentions [19]. Information is recognized mainly by vision, audition, and tactility. However, visualization has the most critical function in human-machine interaction. The virtual information from the robot needs to be transferred and transformed into recognizable visual components, including characters, images, and colors. The design's quality depends on its readability and its ability to show the information [20].

Different types of interfaces can be applied, such as tangible and non-tangible. The tangible interfaces include a mouse, keyboard, and touch screen, and the non-tangible interfaces are based on something, for example, gestures, facial expressions, etc. They all have different purposes, for instance, vehicle control and working with a robot.

Hand gestures can be a valuable and intuitive way to interact with a human-machine interface. Users can communicate with the machine by using natural gestures that people already know how to make, such as pointing, waving, or swiping. However, some considerations exist when designing a human-machine interface that incorporates hand gestures. One important consideration is that the interface should be prepared to recognize the gestures accurately and reliably so that users do not become frustrated with missed or misinterpreted gestures. In addition, hand gestures may not be the best input method for all situations, such as when users must input a large amount of text [21].

Facial expressions can also be used in human-machine interfaces to convey emotions and intentions. There are several ways in which facial expressions are used in human-machine interfaces, including emotion recognition. Facial expressions can be used to detect and recognize emotions in humans, allowing machines to respond appropriately. Facial expressions can also provide feedback to machines on how well they are performing. For example, if a person is frowning or looking confused, a machine may interpret this as a sign that it needs to provide more information or assistance. In addition, they can control machines, such as in virtual reality. Various technologies, such as cameras, sensors, and machine learning algorithms, enable facial expression recognition in human-machine interfaces. These technologies can detect and analyze facial features, such as eye movement, eyebrow position, and mouth shape, to determine the user's emotional state and intentions [22, 23].

Tangible human-machine interfaces are the type of interface that allows users to interact physically with digital systems or machines using physical inputs. These interfaces are designed to make it easier for users to control and manipulate digital information. For example, touch-based inputs (touchscreens), such as taps, swipes, and gestures, are used to manage digital systems. Touchscreens are commonly used in smartphones, tablets, and other mobile devices. They can also provide physical feedback to users, such as vibrations in response to their inputs [24]. However, the workspace where the interface is being used can limit the possibilities, such as lighting conditions and noise level. Besides, limitations can be caused by the operator, such as wearing protective clothing, needing a one-handed or free-handed operation, or safety regulations [25].

The future focus may be on human-machine interaction systems with flexible and wearable components instead of larger electronic devices. Flexible sensors and electric appliances with excellent mechanical flexibility are essential for practicality. Wearable human-machine interfaces rely on precise and adaptable sensors to collect real-time human physiology and environment data. In addition, these systems utilize various communication modes in interactive systems. Wearable HMI systems are currently used in advanced applications such as intelligent identification and security, interactive robot controls, and augmented and virtual reality [26].

1.3 Monitoring of the collaboration

The Human Cyber Physical System (H-CPS) contains the human, physical and cyber worlds. It brings the different parts together by highlighting their strengths [27]. The performed tasks should be monitored to create the Operator 4.0 scheme, and the data should support the operator's activities. By creating an intelligent space [28], these could be possible. While working, it should guide the operator when help is needed. The movements of the operators could be followed by a camera system or real-time locating system to obtain and analyze data on the situation. Incoming data can be processed using artificial intelligence and machine learning solutions [29]. With these, improving process performance and quality is achievable [5].

To keep track of the surroundings effectively, cameras are used for accessibility and cost-effectiveness [30]. However, processing real-time information on limited devices is challenging. It is crucial to extract only essential data from the cameras, especially in complex areas. Using multiple synchronized cameras can monitor complex actions [31]. These systems analyze trajectory data from operator movements, allowing online performance evaluation and identifying potential issues. The results can guide further development in areas where the operator may need improvement.

The cameras part of the monitoring system should be mounted at designated positions to see the workspace. The coordinates of the recognized parts in the camera must be related to coordinates previously determined in the workspace by naming specific points. Calibration can be done by placing markers at distinct positions and estimating their coordinates in the images. [32]

While working, the operator moves in an indoor environment, not just in the immediate area of the robot arm. Indoor positioning systems (IPS) can recognize and track the movements of the relevant objects and humans [33]. The system comprises basic elements (see Figure 1.2). The tag tracks the motion of the worker or objects it is attached to. Anchors are the reference points for the signals coming from the tags. Finally, the server is where the position is calculated with the suitable algorithm [34]. The communication of the systems can be constructed using WiFi, RFID (Radio Frequency Identification), GPS (Global Positioning System), UWB (Ultra-wideband), Bluetooth, or a combination of these. The different types can have various parameters. The range can vary each time, and the chosen type should depend on the longest distance the information travels. There is also a difference in how accurately it can reflect the position. Not all of them can work indoors; satellite-based GPS must have a clear view of the satellites, so it can not work in closed space. It can also be considered what types of infrastructure is already available [35]. The position of these tags, which the locating system uses, can be calculated with different algorithms. The distances can be estimated using the received signal strength indicator (RSSI), and the time of arrival (TOA) [36]. With these tags, the locations of resources are more easily accessible so that they can be obtained more quickly [34]. Time and motion patterns can be found using the locating system on moving

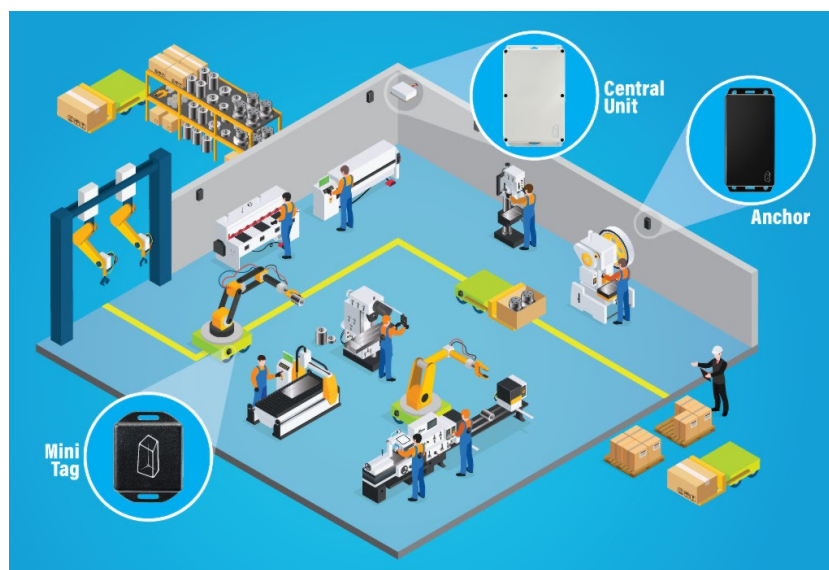


Figure 1.2: The main elements of the real-time locating system

objects. These can vary, and after analyzing the data, the results can be used to increase efficiency or reduce the number of repeated events [37]. Besides, the collected data from the tracked operators can be used to create a better work environment, for example, by changing the task orders or modifying the locations of resources [5] or even monitoring the comfort level of the operators [38].

1.4 Evaluating human-robot interaction

In human-robot collaboration (HRC), various aspects of robots and humans contribute to the overall dynamic. An essential challenge involves devising a comprehensive framework for assessing the collaboration between humans and robots, encompassing all parts of their interaction [39]. Relevant for the effectiveness of HRC is complementing human factors and proper worker training. Adequate training ensures workers can collaborate effectively and safely with cobots, ultimately improving overall efficiency and productivity. Trustworthiness and ethics are vital considerations. Trustworthiness relates to the reliability of the collaborative system to behave safely and predictably. Ethics involves the moral principles guiding collaborative system design and actions. These aspects are critical for ensuring beneficial collaboration between humans and cobots from a broader perspective. Key Performance Indicators such as productivity, efficiency, accuracy, and uptime are crucial in HRC. Humans must retain control over problem-solving and supervision to maintain flexibility, trustworthiness, and machine workload balance. Collaborative robots designed for safe interaction with human workers enhance work cell flexibility, fostering efficient and collaborative human-robot teamwork. Consideration during the design, selection, and development of hardware and automation systems should align with the specific application and role within the HRC system. The Human Digital Twin [40] should be a comprehensive source of truth, encompassing all relevant aspects of the HRC system, including worker-related elements. It is a centralized access point for structured data, supporting monitoring, simulation, training, decision-making, and autonomy functions. Re-configurability management is necessary at two levels. In the short term, the system should adapt to deviations from optimal and safe performance. If short-term adjustments are insufficient, long-term re-configuration actions must be identified and planned, addressing systemic issues that require in-depth analysis and additional efforts [41].

Establishing a "collaboration scale" enables people to assess and contrast various approaches concerning integrating collaborative robots. Additionally, this scale can serve as a valuable instrument for identifying solutions that enhance specific process parameters, such as efficiency or effectiveness [39]. Standard and relevant metrics can be specified for HRC, focusing on robotics systems operating in co-existence, cooperation, and collabo-

ration scenarios with humans. They represent basic, precise, or straightforward variables derived from data collection (such as overall cost and error count) or direct physical measurements in both robots and humans (such as the time taken for a specific action and joint acceleration). These variables clarify the present or concluding condition of the human, robot, process, or interaction. Multiple types of measures can be specified. Time behavior measures indicate the response and processing times required by a human, robot, or a combination of both to execute functions, sub-tasks, or complete tasks. Such metrics include human idle time, algorithm processing time, collaboration time, and task completion time. Process measures encompass facts gathered from the initiation to the completion of a task or sub-task, incorporating cost, workspace design, safety, and product quality elements. Examples of these metrics include the number of errors and the quantity of assemblies achieved. Physiological measures involve values derived from body metrics that offer insights into the current state of the human, such as the acceleration of human joints and heart rate. Human-robot physical measures entail values from sensors that reflect the ongoing state of interaction, such as the distance between the human and the robot [42].

Chapter 2

Developed framework

Analyzing and understanding human behavior plays a big part in designing more efficient robotic systems. The developed use case for monitoring the collaboration between the operator and robot is presented through a game. In this scenario, the robot represents the collaborative partner.

It is a two-player board game where the players are the human and the robot. They share a workplace where they play against each other. A board and pieces to play with are needed to set up the play area. These must be suitable for the robot to pick up and place the pieces on the board smoothly. To accomplish this situation, the game has a solving algorithm to determine the next step. The algorithm serves as the robot control. The tasks are to manage the robot arm's motions so it can do its job to be a proper opponent and the game can flow without interruptions.

The results from the algorithm that calculates the next step are transformed for positions for the robot arm so it can move to the determined place. While playing, not only the robot arm is moving and performing tasks. Measuring the operator's movements and reactions is also one of the tasks. The basic tic-tac-toe game is relatively simple, with two players taking turns placing their pieces. However, adding a treasure hunt element to the game can make it more complex. The tic-tac-toe pieces for the human player are hidden, so they have to find them to make their next move. Therefore, the player is standing next to the board and moving inside. The help of an indoor positioning system's (IPS's) tags is used to help the finding process. An alternative version of the game involved first creating a pre-established pattern multiple times at the start to study the learning process. Following this, participants played a tic-tac-toe game against a robotic arm, similar to the earlier version. Meanwhile, when it was not playing the tic-tac-toe game, the robotic arm replicated the pattern generated by the human participant in the previous phase.

In most cases, the robot and the operator work in separate spaces without much interaction and influence on each other. However, working together can enhance the ability of

both robots and humans. Therefore, monitoring where the operator and the robot work together is essential for collaboration.

When robots and humans work in the same workspace, their movements should be monitored and observed because they have valuable information for future use. This is done using a camera, an IPS, and wearable sensors, which together form a framework, as seen in Figure 2.1, for monitoring and observing the movements and events of both the human and the robot. The defined workspace, which represents the created collaborative space, is where the operator and the robot arm work together to complete a task. The operator is responsible for the primary goal, with the robot arm supporting the task. Therefore, the movements of both the human and the robot arm impact the workspace and the task at hand. By monitoring and analyzing their movements, valuable insights can be gained to improve performance, safety, and efficiency.

The camera and the IPS are intended for observation. A camera is positioned above the workspace to record the current events. Depending on what the robot arm is doing, the operator's actions may vary, and with a camera system, these changes can be observed. The camera captures images of the workspace and detects changes in the environment, such as the objects' location and movements of the human operator and the robot arm. The changes can include how the human operator moves their arm, how they place the

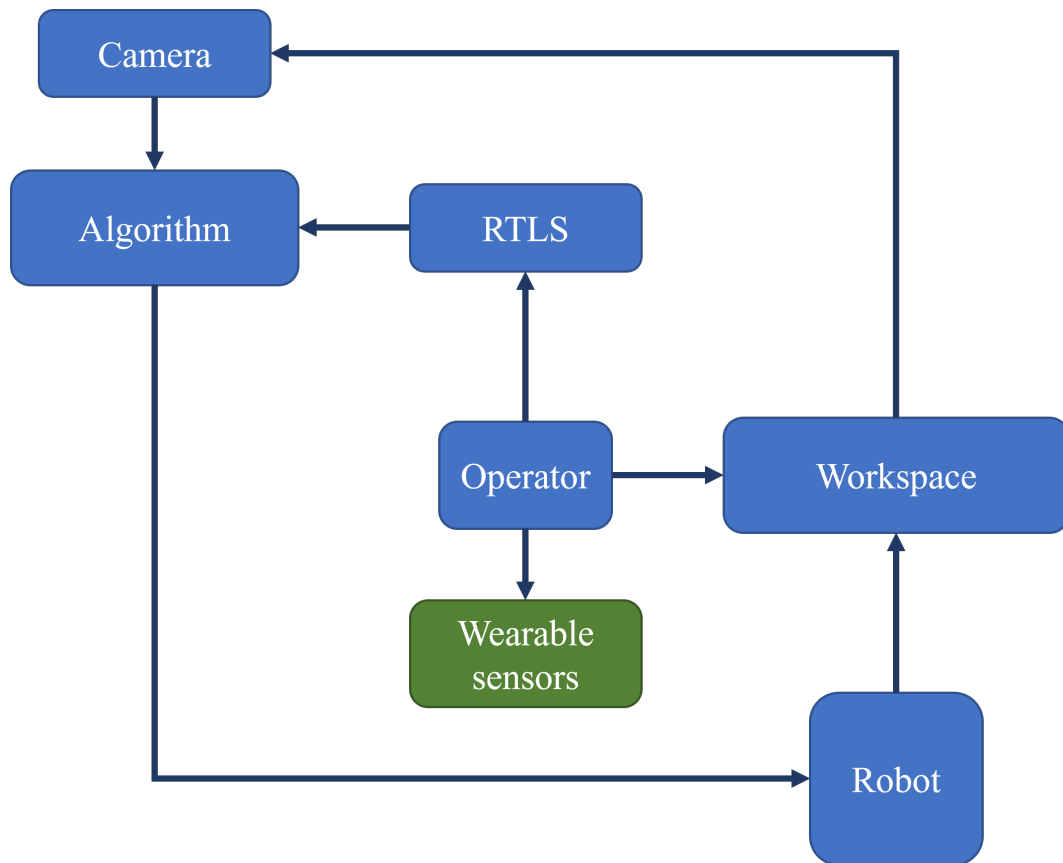


Figure 2.1: The developed framework

next part, and from which direction. Besides, the camera can detect the current status of the workspace. These results are one of the identified positions on the board. In addition, the information is saved on who performed each step. The input for an algorithm is determined from the positions the camera detects. These inputs are the previously mentioned motion changes and the current status of the workspace. The board's previous status is saved in a matrix containing positions and information on whether the human or the robot did the step. The algorithm can calculate what will happen next with this camera input about the workspace's status. The algorithm output is responsible for the robot arm's following act, which is position data of where the robot will move next.

The operator works near the robot arm and collects the necessary parts. Finding different parts can take different times, determining when the robot arm's following action will happen. While the operator is searching for the next part with the help of the tracking system, the robot can work on other things in the meantime. The tags of the IPS indicate the positions where the operator should go for the next piece. Knowing the average time needed to find the next part, the next task of the robot can be determined. This way, the robot does not have idle time and does not need to wait for the operator to do the next task.

As seen in Figure 2.1, the wearable sensors box is a different color because in the future, besides the camera, I plan to add the possibility of measuring physiological signs.

Chapter 3

Use cases and the developed workspace

The developed use case for monitoring the collaboration between the operator and robot is presented through a game. First, the player builds a predefined pattern several times until they reach a level where they make the pattern in about the same amount of time. After they play a tic-tac-toe game, it is a two-player board game where the players are the human and the robot. They share a workplace where they play against each other. A board and pieces to play with are needed to set up the play area. These must be suitable for the robot to pick up and place the pieces on the board smoothly. To accomplish this situation, the game has a solving algorithm to determine the next step. The tasks are to manage the robot arm's motions so it can do its job to be a proper opponent and the game can flow without interruptions. The results from the algorithm that calculates the next step are transformed for positions for the robot arm so it can move to the determined place. While playing, not only the robot arm is moving and performing tasks. Measuring the operator's movements and reactions is also one of the tasks. When not playing tic-tac-toe, the robot builds a pattern.

3.1 Description of the pattern building game

In this game, players are presented with a predetermined pattern (as seen in Figure 3.1) they must create. Pattern building helps compare robot and human work capacity and performance. This design is formed using eight cubes of various shapes and colors. The players are introduced to this pattern for the first time. The process of assembling the pattern continues until players reach a level where they consistently complete the task in nearly the same amount of time. This progression indicates a mastery of the game as players become adept at arranging the cubes. As players engage themselves in the game, they are not only tasked with replicating the visual pattern but also with strategizing their cube selections and placements. The familiarity with the cube locations allows players to

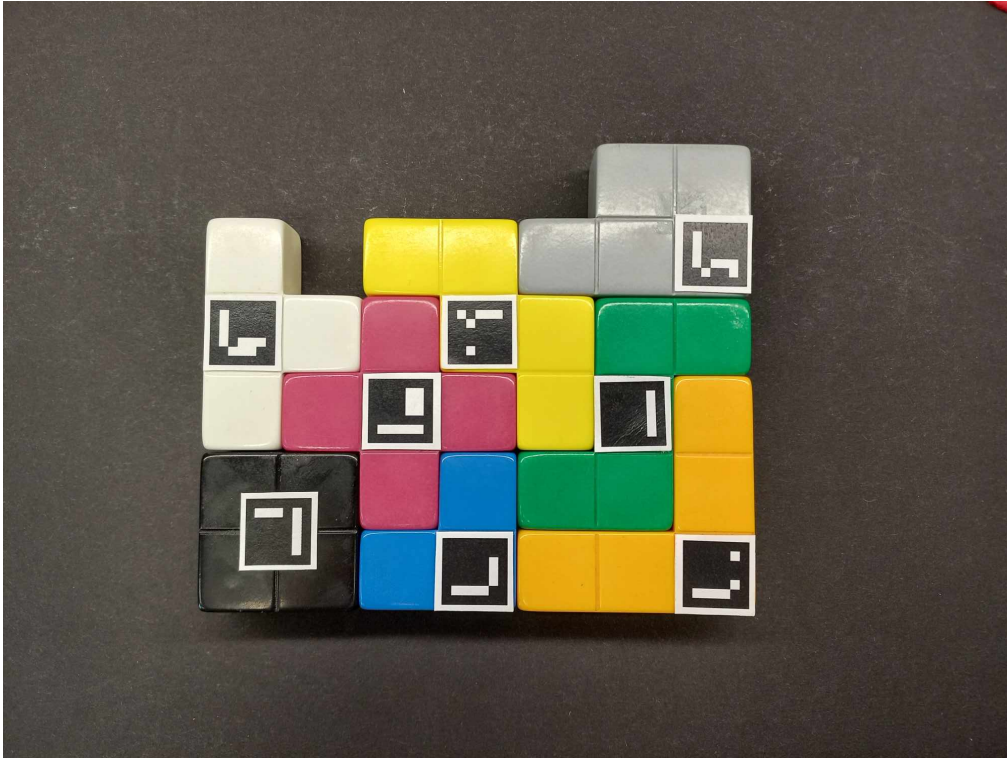


Figure 3.1: The predefined pattern of the building game

develop tactics and optimize their approach.

Each cube is marked with an ArUco code attached to its top surface, allowing the camera to recognize whether the pattern has been correctly assembled. Each ArUco code is associated with a unique numerical identifier, which can be identified using the corresponding OpenCV library. The integration of ArUco codes serves a dual purpose. Firstly, it verifies whether the pattern has been successfully reproduced. Secondly, it provides a means of assessing the accuracy of the player's arrangement. To achieve this precision assessment, a reference image is initially created. In this reference image, a specific orange cube is selected as the anchor point. The angles at which the other cubes are arranged are calculated relative to this anchor point. This reference data serves as a benchmark for evaluating subsequent attempts. As the player completes the pattern, real-time analysis is performed on the arrangement using the ArUco codes. The angles of the cubes in the assembled design are compared to those in the reference image, and the system calculates the deviation. To account for slight misalignments due to human error, a tolerance threshold is set. If the estimated deviation falls below this threshold, the system confirms the accuracy of the pattern. Conversely, if the deviation exceeds this threshold, the system detects a misalignment in the arrangement.

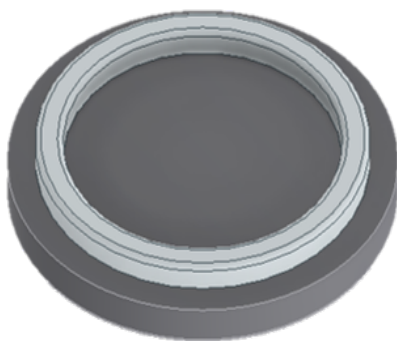
3.2 Description of the developed collaborative game

Tic-tac-toe is a two-player strategy board game. This collaborative game is for measurements during the collaborative process. Traditionally, the two players play with X and O -shaped pieces and take turns placing their marks on the 3×3 board on any remaining free space. The winner is the one who manages to place three pieces in a line, horizontally, vertically, or diagonally.

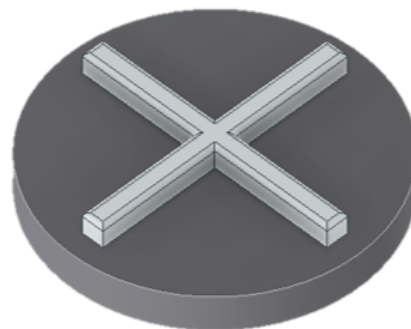
In this case, one player is the human, and the other is the robot arm. While playing, an algorithm calculates the next move of the robot arm, and a camera monitors the state of the game and gives feedback. For example, the human player places the first piece on the board, and after the camera's algorithm recognizes where it was placed, the game solver algorithm can calculate the next act of the robot arm.

The Python package that determines the next step uses the minimax searching algorithm to simulate every possible move and counter-move [43]. This way, depending on the current game state, it will always pick the best move. The program was initially designed to test the effectiveness of each algorithm by simulating multiple games and showing how each algorithm held up against the other. However, it was modified to play only one game, with one of the inputs being the human player's movement and the other the algorithm's.

In order to play against the robot arm, a board and the X and O pieces are required. The pieces had to be of a size and shape that could be easily picked up by the robot arm and stacked on top of each other. With the circular shape, even if the robot rotates it, they fit. As shown in Figure 3.2, both pieces' bases are black with the X and O shapes in white on top of them so that the camera can see them. The 3-dimensional model was made, and the plastic discs were printed with a 3D printer, 5 – 5 each, so either could start. The inside of the pieces is hollow so that they can be stacked on top of each other



(a) O pieces



(b) X pieces

Figure 3.2: The model of the pieces for the game

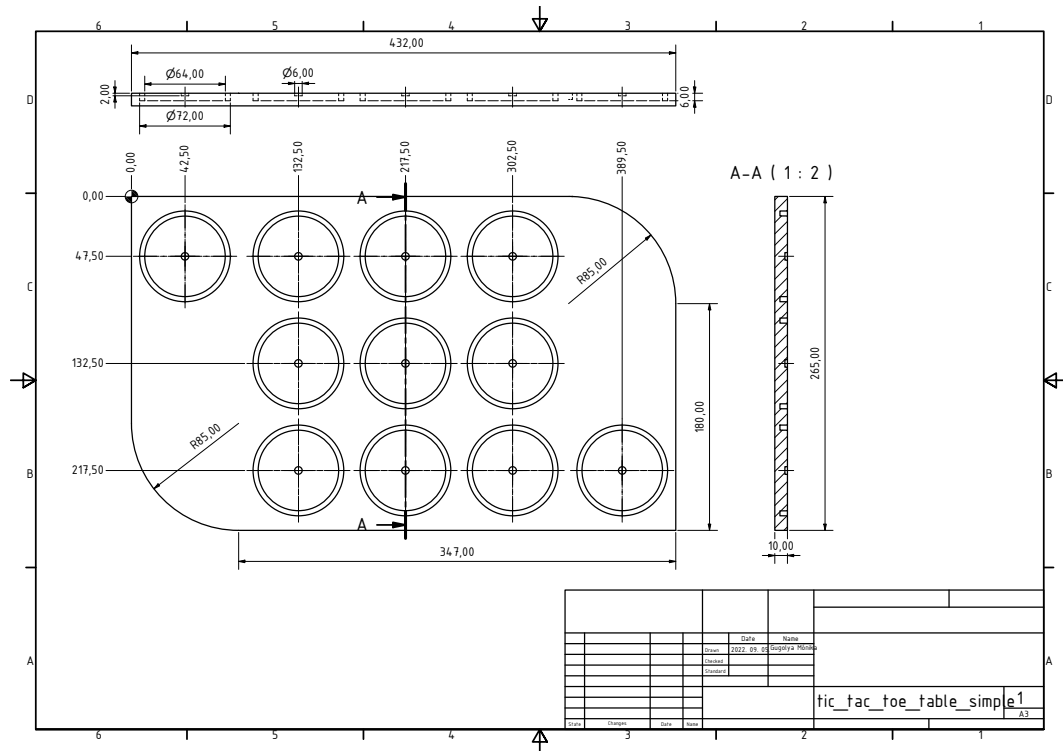


Figure 3.3: The technical drawing of the board

and take up less space.

In designing the board, it had to be considered that the discs always had to be in the same position so that the camera could recognize the positions. Therefore, slots were created for the pieces to fit into and on either end for storing them. The depth of the holes is less than the height of the discs so that they can be easily removed. The size of the board is such that it fits on the table holding the robot, and the robot arm can access all positions. After designing the board and making the technical drawing, seen in the Figure 3.3, it was sent to a company that helped make it. The board was painted black (similar to the bases of the pieces), so the camera could easily separate the white X -s and O -s.

The camera is positioned at the end of the board in the middle to see what is happening, which can be seen in Figure 3.4. It is mounted on a pole above the board and connected to the computer via USB. OpenCV is the Python package that detects the game's current state with a camera. There are four red dots on the edges of the three-by-three square where the pieces are to help the camera focus, as the Figure 3.5 shows. After detecting the current game's status, it returns the positions to the algorithm. A downside of using camera recognition is that it is affected by lights. To eliminate this problem, the function of the camera is called multiple times. With the help of the matrix containing the board's previous status, the board recognition function is called until there is only one difference between the current and previous status matrix.



Figure 3.4: The developed workspace

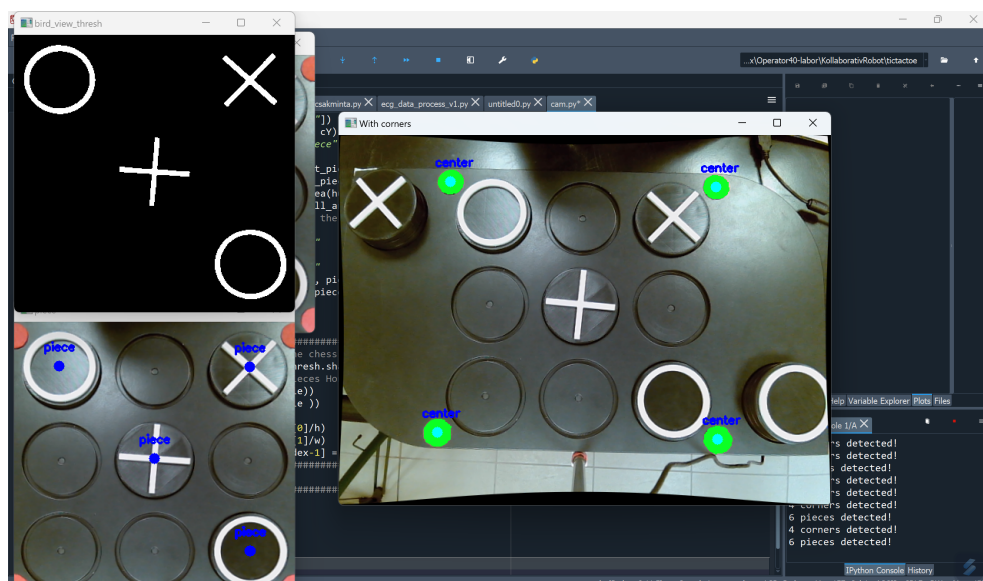


Figure 3.5: The tic-tac-toe game's state recognition program

3.3 The applied UR5 robot arm and the developed scenario

The robot arm used is a Universal Robots company's UR5 model, a collaborative robot. A safe collaborative workspace can be achieved with the help of a collaborative robot. The robot arm can be programmed from its own teach pendant, but it is limited. Simple movements, picking up, and placing can be programmed from there. Sensors could be used for the signals, but the options are finite; for example, image recognition is impossible. So, to play the tic-tac-toe game, another programming interface was needed. The programming interface used is Python because there are a lot of open-source packages that can help create the situation. One of these packages is the urx Python package. With this package, it is possible to program the robot arm from a computer by connecting the computer and the robot to the same network. This way, making more complicated programs with the robot arm, like the tic-tac-toe game with camera recognition, is possible. Similar to the programming with the teach pendant, instructions can be given, like moving the robot and opening or closing the gripper.

The nine places the pieces could go for the game had to be determined. By fixing the board to the table of the robot, these positions always remained the same; they did not need to be calibrated every time. After moving the robot to the specific places, the coordinates were saved in the Python program labeled with the locations. Similarly, the storage positions were defined, from which the robot takes the pieces.

The robot and the player move in the same space as they play against each other on the board. While the human can move out of the robot's route, the robot can not do that if the player is in the way and does not pay attention. The advantage of collaborative robots is that they do not have sharp edges, and colliding with something (even with less force) causes a protective stop. This way playing against the robot arm is relatively safe.

3.4 Movement tracking with indoor positioning system

The basic tic-tac-toe game is relatively simple, with two players taking turns placing their pieces. However, adding a treasure hunt element to the game can make it more complex. The tic-tac-toe pieces for the human player are hidden, so they have to find them to make their next move. Therefore, the player is not just standing next to the board but also moving inside. The help of IPS tags are used to help the finding process and to track the movements of the participants, and it can be visualized as seen in Figure 3.6.

This indoor positioning system uses ultra-wideband for communication. The data obtained from the system is an X and Y coordinate of the tag and the signals from the

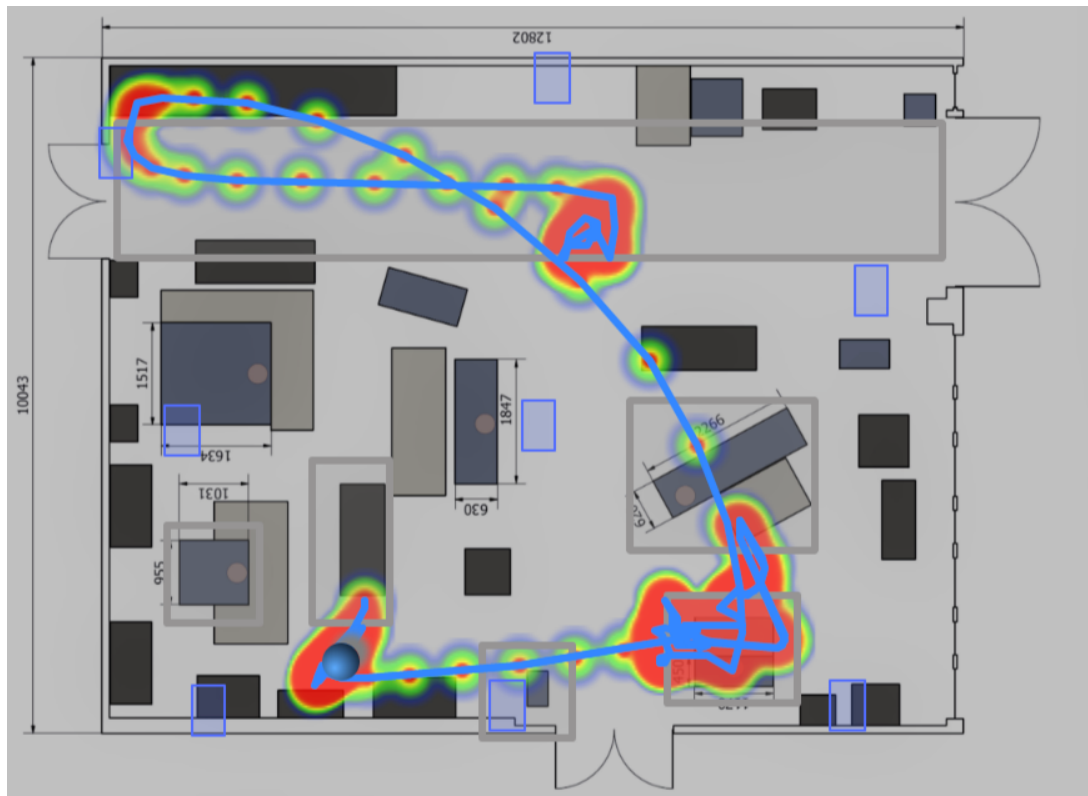


Figure 3.6: The movement of the player

sensors in it. The system can determine the location of the tags with an accuracy of 50 centimeters. There is an internal LAN network and eight anchors that gathers the data. A central unit collects this information and forwards it to the cloud server, where the position calculations are done.

3.5 Human activity monitoring and evaluation method

In human-robot collaboration, one crucial aspect is knowing what the worker is doing. This information is essential for scheduling, planning, and managing tasks effectively. To achieve this, I rely on making observations, which can be divided into categories. Firstly, I have micro-movements. This refers to workers' small, subtle movements while performing tasks, such as placing and picking up parts. Secondly, I have macro movements captured through indoor positioning systems. This observation category refers to workers' more substantial, prominent movements while navigating a workspace. IPS data can help us understand the worker's movements through the space, and I can use this information to optimize their path or avoid potential collisions.

The IPS's tag indicates the location of these hidden parts. This way, the pieces can be hidden somewhere different every time. The positions are displayed on a monitor to help the player find them. The player also has his tag to track his movements while searching

for the disks.

The system can visualize the movement of the player while they are searching. The room has a floor plan with all the furniture and equipment shown, and the route can be displayed on this. For example, it can be seen where the player moved, where they spent more time searching for the piece, and which route they took. Different players have different tracks, and these take various times.

The coordinates can be used to calculate the Euclidean distance (d) between two points and then summed to calculate the total distance walked. In the Euclidean plane, the points have Cartesian coordinates. Then the distance between beginning $A(p_i^1, p_i^2)$ and the end $B(p_{i+1}^1, p_{i+1}^2)$ can be calculated, where i is the number of points.

$$d = \sqrt{(p_{i+1}^1 - p_i^1)^2 + (p_{i+1}^2 - p_i^2)^2}, i \in \mathbb{N} \quad (3.1)$$

As the analysis of micro-movements and macro movements through indoor positioning systems provides valuable insights into workers' activities in human-robot collaboration, my evaluation method builds upon these observations by introducing a game-based scenario to assess the efficiency, adaptability, and collaborative synergy between humans and robots, incorporating quantitative measures such as time to evaluate the dynamics of collaborative work comprehensively.

Unlike traditional evaluations that rely solely on quantitative measures, my approach introduces an environment that mirrors real-world collaborative scenarios. Through a series of tasks, including pattern building by humans, robot playing tic-tac-toe, human playing tic-tac-toe, robot building pattern, and human searching in the lab, I aim to evaluate the efficiency, adaptability, and collaborative synergy between the human and the robot. Furthermore, including time as a pivotal metric adds a quantitative dimension to the evaluation. Timing each task provides insights into the efficiency of both human and robot collaborators and analyzes their respective strengths and areas for improvement. The emphasis on time also aligns with the dynamic nature of collaborative work, where swift and precise actions often define success. Including physiological metrics will add a layer to the evaluation, offering insights into the well-being of the human collaborator.

Chapter 4

Experiment at the Operator 4.0 laboratory

Two targeted measurements were performed. These experiments aim to understand human behavior and develop an evaluation system for collaboration. In the first measurement, 15 participants played a tic-tac-toe game against the robot. As seen in Table 4.1, ten men and five women of varying ages participated. They come from different scientific fields and have different educational backgrounds. During the measurement, the robot started the game, followed by the player, who had to find the pieces needed for each move. The parts were hidden in the same place each time, so it can be compared to how long it took to complete the game. The aim is to adapt the robot's trajectory to the movement of the human hand, and while the operator is looking for the next part, the robot can do

Participant	Field	Education level	Birth year	Gender
P01	Mechatronics engineering	BSc student	1995	Male
P02	Environmental engineer	PhD	1988	Male
P03	Mechatronics engineering	BSc student	2000	Male
P04	Finance and accounting	BSc student	2000	Female
P05	Chemical engineer	PhD student	1983	Male
P06	Mechatronics engineering	PhD student	1996	Male
P07	Chemical engineer	PhD	1992	Male
P08	Mechatronics engineering	BSc student	1999	Female
P09	Engineering Manager	PhD student	1997	Female
P10	Mechatronics engineering	BSc student	2001	Male
P11	Tourism and catering	BSc student	2001	Female
P12	Bioengineering	PhD student	1989	Male
P13	Mechatronics engineering	BSc student	2019	Male
P14	Chemical engineer	PhD student	1998	Female
P15	Computer science	BSc student	1999	Male

Table 4.1: The participants at the targeted measurement

Measured data	Tool	Unit of measurement
Hand movement	Web camera	-
Path taken	IPS	-
Player's time	Phone application	seconds
Robot's time	Computer	seconds
Pattern learning time	Stopwatch	seconds

Table 4.2: The measured data

other tasks.

In the second measurement, four individuals participated. Initially, a predetermined pattern was built multiple times to observe the learning process. Subsequently, similar to the previous measurement, participants engaged in a tic-tac-toe game against the robotic arm. The distinction in this case was that while the participants were not making moves in the tic-tac-toe game, they were searching for their next piece to be able to play their next move. Meanwhile, the robotic arm replicated the pattern the human participant made earlier.

In Table 4.2, a comprehensive overview of the measured data, corresponding tools, and units of measurement is provided. The table captures various aspects related to evaluating a system or process. The measured data includes hand movement, path taken, player's time, robot's time, and pattern learning time. The tool used to capture hand movement is a web camera. The IPS is employed to record the path taken during the task. Both of these measurements are fundamental in understanding the spatial dynamics of the system under consideration. The player's time, indicating the duration taken by a human participant is measured using a phone application. On the other hand, the robot's time is measured using a computer. It was saved when the different movements of the robot were made. These time-related metrics offer insights into the efficiency and speed of both human and machine components. Additionally, the table includes the pattern learning time measured using a stopwatch. This parameter signifies the time required for the system to grasp and understand patterns. The unit of measurement for the player's time, the robot's time, and pattern learning time are in seconds, highlighting the precision of the temporal measurements.

In the next chapter, it will be detailed how the two scenarios can be integrated.

4.1 Learning curve

In this part of the experiment, four participants engaged in a pattern-building game, completing the predefined puzzle 10-20 times. With only four people, the sample size is small. However, in Chapter 5, I will explain how the experiment's design will allow for measurements with larger sample sizes. The primary objective was to observe any patterns in the participants' performance over successive attempts, focusing on the time to complete the task.

Figure 4.1 shows that the participants learn the process within 10-15 iterations, as can be seen from the fact that they are getting consistent times.

As the experiment progressed, participants showed a pattern of improvement that eventually slowed down, resulting in smaller and smaller reductions in completion time. While most participants improved similarly, individual differences were noted. Initially, everyone took around 20 seconds or more to complete the task, but one participant finished the task remarkably quickly.

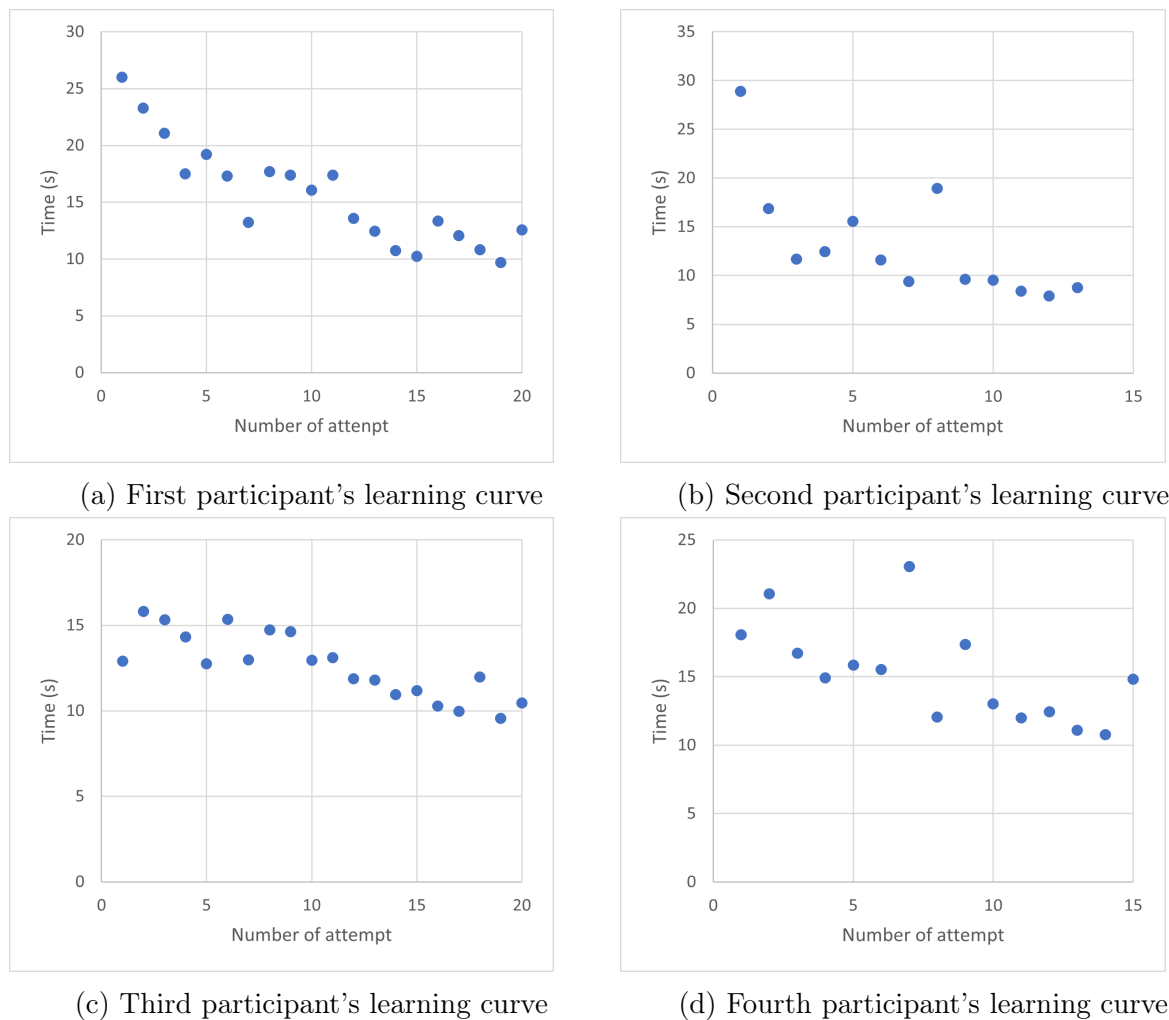


Figure 4.1: The learning curves

This pattern of improvement indicates a combination of explicit and procedural learning. Participants quickly acquired the skills needed to complete the task but eventually reached a point where further improvement became incremental, indicating the establishment of procedural memory.

The diminishing rate of improvement raises questions about whether fatigue or other factors, such as boredom or monotony, influenced performance. It is essential to consider whether participants reached a cognitive limit.

This research has implications for developing robotic systems that can emulate and adapt to human-learned skills. In scenarios requiring repetitive or precision tasks, such as manufacturing or assembly, this approach can optimize robotic performance.

4.2 Micro movements

The movement of the player's hand in the workspace has a more significant impact on the robot. From the video footage, a lot can be determined. The primary is to observe the path of the hands. Then, the path can be visualized using video analysis, and image coordinates of the path can be obtained.

To improve collaboration, a robot's trajectory should be designed to avoid the areas where the human hand most frequently moves during gameplay. This was achieved by analyzing the trajectory of the hand's movement and identifying the areas on the game board where it occurred most often. Then, the results were plotted on a heatmap as seen in Figure 4.2, with warmer colors indicating higher frequency areas. Most hand

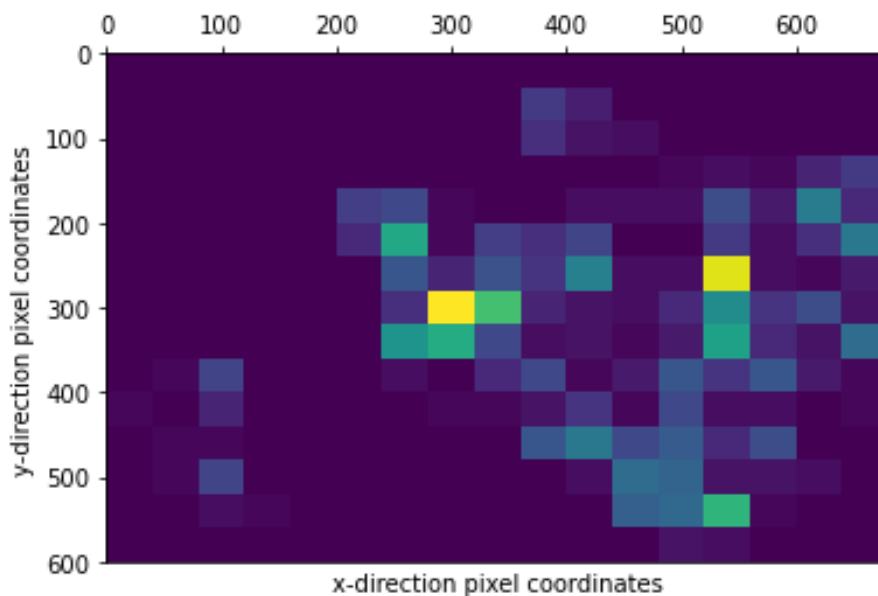


Figure 4.2: The most frequent trajectories

movements occurred in the middle and right side of the board, with only a few occurring in the bottom left. Based on this information, the robot can be programmed to avoid these areas as much as possible.

Besides, it can be observed if there is a difference between using the right or left hand for placing the pieces. Therefore, the videos were categorized based on whether the hand in question was the left or right hand. Then, the trajectory coordinates were plotted accordingly, as seen in Figure 4.3, the left ones being green and the right ones blue. Upon analyzing the resulting data, distinct differences were observed in the trajectory patterns between the left and right hands. Specifically, most left-hand movements occurred on the left side of the board, while right-hand movements tended to occur more frequently on the upper right-hand side. This information provides means of predicting whether a particular trajectory was made by the left or right hand.

In addition to analyzing hand trajectory, the speed was also examined at which the hand moved during the game. By analyzing the speed of the hand, further insight could be gained into the cognitive processes involved in decision-making during the game.

To do this, the coordinates of the hand were obtained at the same frequency, allowing for a comparison of the speed of movement at different points in time. The results showed that the hand moved more quickly at the beginning of a move, indicating that the participant had yet to decide where to put their piece. Once they had decided on a move, the movement speed decreased as they carefully placed their piece on the board. Finally,

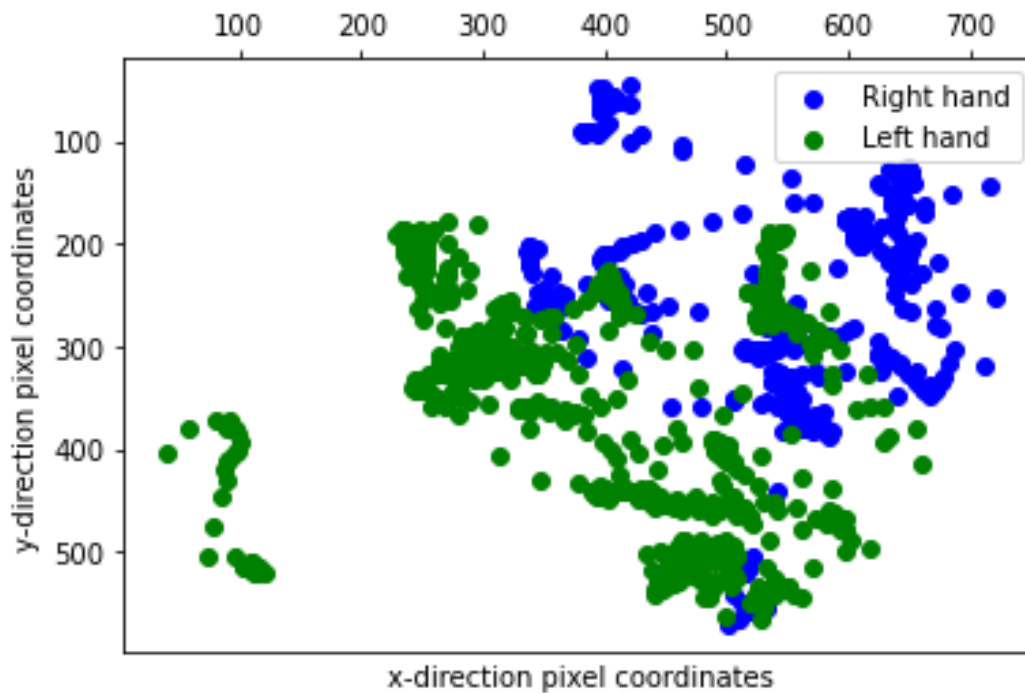


Figure 4.3: Right and left-hand coordinates

once the piece had been placed, the movement speed increased as the participant retrieved their hand. These findings highlight the complex cognitive processes involved in decision-making during the tic-tac-toe game. By analyzing the trajectory and speed of hand movements, a more comprehensive understanding of human behavior during gameplay can be gained. This information can be used to develop more sophisticated robotic systems that can better anticipate and respond to human actions.

4.3 Macro movements

The tic-tac-toe game was enhanced by having the players' pieces hidden, similar to a treasure hunt, and the tags were employed to help their finding. Furthermore, one tag was placed in the players' hands to enable path monitoring during the search so their path during searching can be visualized. The obtained coordinates from the tags were plotted on a simplified laboratory map. This allowed comparison of the different paths taken by the players. As seen in Figure 4.4, most of the movement happened in the area of the robot, in the middle, because they had to bring all their pieces back and place them. The four pieces for the player were hidden on the far upper left shelf, one at the table in front of it; the other two were on the right side at the drill in the far left and under the table next to the robot on the left. Although, as shown, a few paths are down in the middle, where there were no hidden pieces, most of the searching happened in the right place.

The time and walked distance can be calculated from the IPS's tag data. As seen in Table 4.3, some people were slower and some faster, but generally, walking more took

Participant	Walked distance (m)	Time
P01	67,46	2:09
P02	50,46	1:59
P03	49,16	1:29
P04	55,04	2:23
P05	55,61	1:54
P06	58,29	1:43
P07	68,09	2:26
P08	62,12	2:07
P09	52,49	1:49
P10	51,21	1:41
P11	47,50	1:49
P12	45,40	1:56
P13	59, 81	1:59
P14	51,17	2:04
P15	69,39	2:31

Table 4.3: The walked distance and the time it took

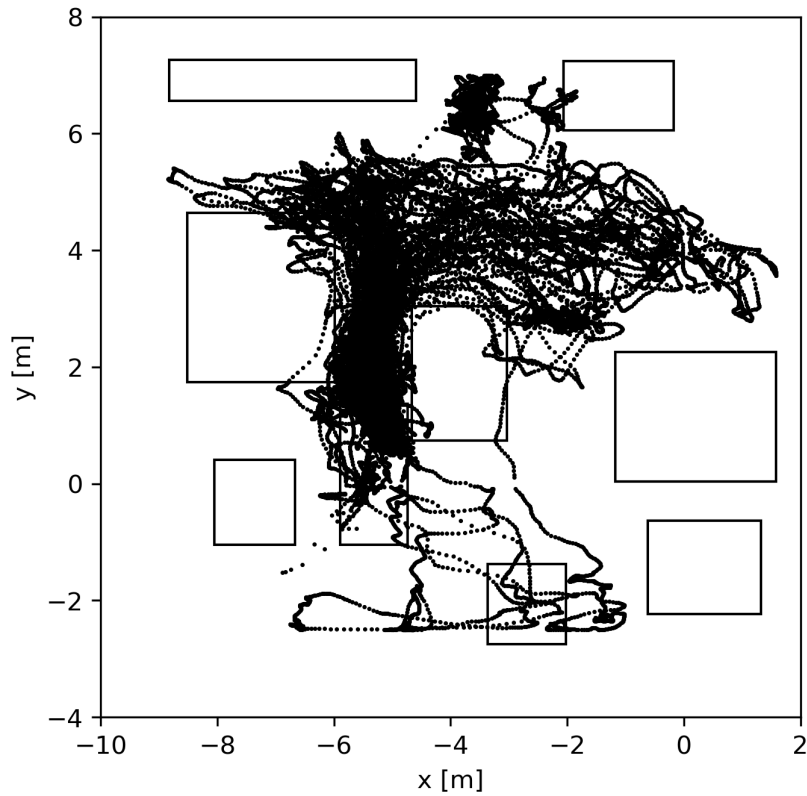


Figure 4.4: All position of the player movements

more time.

Although it was not part of the task to evaluate the physiological signals, Figure 4.5 can be seen as an example of how it can be integrated, for example, by watching how the heart rate changes during the task.

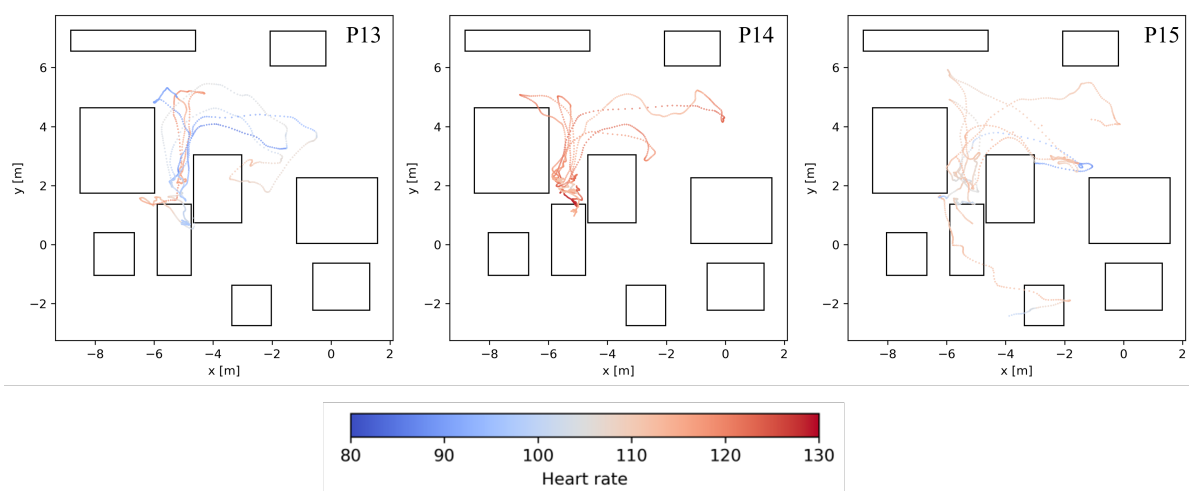


Figure 4.5: The movement of the players with their heart rate at the time

4.4 Task characteristics

The previous chapters have shown what was measured. For the micro movements, there was a correlation between the trajectory of left or right-handed placing, and the most frequented part of the workplace was also identified. For macro movements, it was shown who took the least time and walked the least distance, so the most efficient way to pick up the pieces could be found. There is no significant correlation between the observed values mentioned and the outcome of the tic-tac-toe game in Table 4.4.

A Gantt chart is a horizontal bar chart that visually represents project schedules, tasks, and timelines. It shows project activities, durations, and interdependencies between tasks in a clear and intuitive format. The primary advantage of a Gantt chart lies in its ability to communicate complex project timelines and task sequences straightforwardly. Each task is represented by a horizontal bar, the length of which corresponds to the task's duration. The bars are arranged chronologically along a timeline. The four tasks are the piece searching by the person, the pattern building by the robot, and the tic-tac-toe game against each other. This visual representation will offer a more comprehensive view of the collaborative dynamics, highlighting not only the active task durations but also the periods of inactivity and waiting. This information can be critical in optimizing the human-robot collaboration for enhanced efficiency and user experience.

The measurements have been evaluated, and one of the essential parameters for collaborative working is time and the pace at which the human and robot work together. In my scenario, Figure 4.6 serves as a comprehensive visual guide, showing the dynamics of

Participant	Game mode	Result
P01	Hard	Lost
P02	Hard	Lost
P03	Hard	Lost
P04	Medium	Draw
P05	Medium	Draw
P06	Medium	Draw
P07	Medium	Draw
P08	Medium	Draw
P09	Medium	Lost
P10	Easy	Draw
P11	Easy	Won
P12	Easy	Won
P13	Easy	Won
P14	Medium	Draw
P15	Medium	Draw

Table 4.4: The results of the games

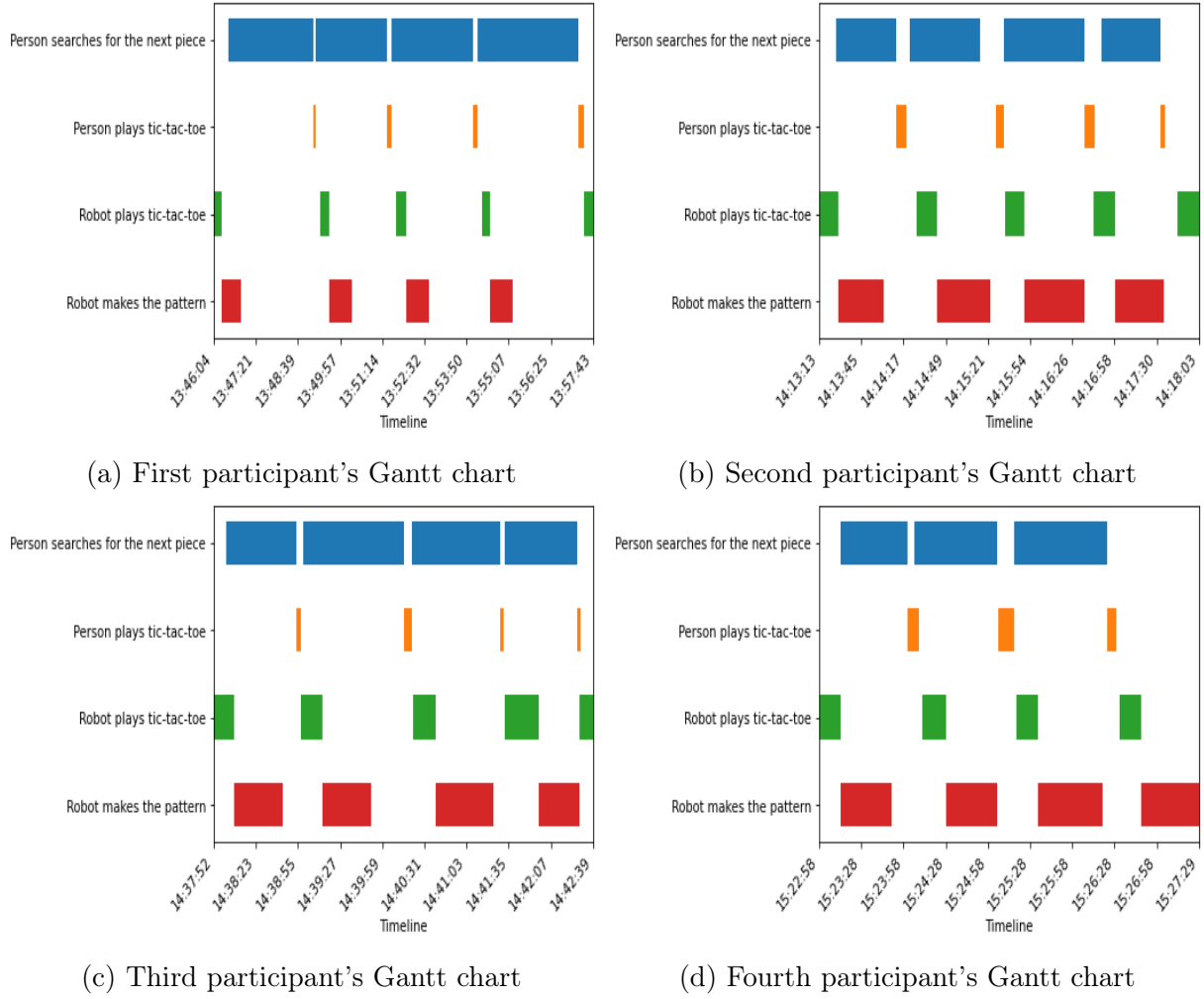


Figure 4.6: Gantt charts for each person

collaborative interactions during the distinct tasks.

The four tasks:

1. The participants build the predefined pattern multiple times until they are consistent.
2. The human and the robot engage in a tic-tac-toe game. They share a common workspace and compete against each other. The game involves strategic moves and decision-making, not only for the human but also for the robot, which utilizes an algorithm to determine its next move. The time taken for each move and the overall game duration are measured to assess the collaborative performance.
3. In between rounds of tic-tac-toe, the human participant searches in the lab for their next piece.
4. While the human searches for their next piece, the robot autonomously participates in a pattern-building activity. This phase not only showcases the robot's ability to

execute tasks independently but also serves as a comparison point with the human-operated pattern-building task. The time taken for the robot's pattern-building activity is a crucial measure of its autonomous capabilities.

This visualization exposes active task durations and critical intervals of inactivity and waiting, providing insights to optimize human-robot collaboration for heightened efficiency. The Gantt chart does not show the building pattern as it occurred separately from the other three tasks. Additionally, the tic-tac-toe game was divided into two tasks, one for the person and one for the robot. After analyzing the Gantt charts of all four participants, a significant observation can be made. The task that consumed the most time was the human's search for their next tic-tac-toe piece. The consistent sequence in which the robot built its pattern remained uniform. The robot's placement of the tic-tac-toe piece displayed a relatively consistent duration, fluctuating slightly based on the specific placement location, ranging between 15-18 seconds. Additionally, variations were evident in the time participants took to contemplate their next move, highlighting the personalized nature of decision-making in the gaming context.

The robot and the participants built the same pattern so their time could be compared. They picked up the pieces from the same place. On average, the first step of the person took around 20-25 seconds and went down to 10-15 seconds. The robot was slower than this; placing two of the cubes took about 35-45 seconds; in total, it took 157 seconds to finish the pattern. The cause of this is the robot's speed, which is much slower. Notably, the game durations ranged from 5-10 minutes, with the robot consistently waiting for the human to progress in the task at hand. While the last participant's game was shortened due to the robot winning, the other three participants experienced drawn games, none claiming victory. The collaborative gaming experience achieves a balance between the human participant and the robot. However, the robot must often pause to synchronize with the human's pace. Gantt charts provide a visual representation of temporal dynamics and valuable insights into the factors that influence human-robot collaboration. By highlighting these factors, Gantt charts help to improve collaborative efforts, making them more seamless and efficient.

Chapter 5

Design of experiment

In exploring human-robot collaboration, I present a designed use case centered around a collaborative gaming scenario where an operator interacts with a robot. This scenario encompasses four tasks: pattern building by the human, tic-tac-toe game between the human and the robot, searching for the next piece by the human, and the robot's independent pattern-building activity. Each task is unique, through which I can observe and measure the collaborative dynamics between the human operator and the robotic system.

In this chapter, I will create an experimental design based on the measurements. I will use the data from the measurements to develop a plan for conducting experiments and analyzing the results. Several key factors can be considered to monitor the collaboration:

1. **Tic-tac-toe piece hiding place level:** In this factor, different hiding places as difficulty levels are considered - Easy, Medium, and Difficult. The variable to be measured includes the time the player takes to complete each task at varying game levels, along with the accuracy and instances of task interruptions.
2. **Pattern Complexity:** This factor involves manipulating the complexity of predefined patterns, categorized as Simple, Moderate, and Complex. The variables to be measured encompass the time taken to construct predefined patterns, accuracy in pattern-building, and any interruptions encountered during this task.
3. **Task Order:** Task order variation is introduced with two levels - Pattern Building First, followed by Tic-Tac-Toe / Tic-Tac-Toe first, followed by Pattern Building. The variable to be measured is the impact of task order on the time taken, accuracy, and any interruptions experienced during the tasks.
4. **Robot's Algorithm Efficiency:** This factor explores the efficiency of the robot's decision-making algorithm at three levels - Low, Medium, and High. Variables to be measured include the time the robot takes to make decisions in the tic-tac-toe

game, the accuracy of robot moves, and any interruptions associated with algorithm efficiency.

5. **Workspace Setup:** The arrangement and suitability of the workspace are considered at two levels - suitable and suboptimal. The variable to be measured is the efficiency of the robot arm in picking up and placing pieces and the overall impact on task performance.
6. **Operator's Familiarity:** Operator familiarity is categorized into three levels—Novice, Intermediate, and Expert. Variables to be measured encompass how the operator's familiarity influences task time, accuracy, and reactions during collaborative tasks.

Variables to be Measured:

1. **Time Taken:** Time taken for each task (tic-tac-toe, pattern building, searching for the hidden piece) is measured in minutes or seconds.
2. **Idle Time:** Total idle time during the collaborative tasks, measured in minutes or seconds.
3. **Frequency of Idle Periods:** The number of instances where either the human or the robot is in an idle state.
4. **Reasons for Idle States:** Categorize and measure the reasons for idle time, such as waiting for instructions, processing delays, or task completion.
5. **Accuracy:** Accuracy is the percentage of correct moves or task completion for tic-tac-toe, pattern-building, and searching for the hidden piece.
6. **Task Interruptions:** Task interruptions are measured by frequency and duration, capturing any disruptions in the flow of tasks caused by errors or external factors.
7. **Operator's Movements:** Operator movements are measured through position tracking and a camera, providing insights into movement patterns during the tic-tac-toe game.
8. **Robot Arm's Efficiency:** Robot arm efficiency is measured by the smoothness of motions and successful task completion, evaluating its performance in picking up and placing pieces.

The measured variables provide insights into task efficiency, engagement levels, and the impact of different factors on human-robot collaboration. The proposed experimental design is a foundation for conducting large-scale measurements and obtaining comprehensive data on the collaboration between humans and robots.

Chapter 6

Conclusions and further steps

Observing the operator allows the scheduling and optimization of the robot arm. One way to achieve this is by monitoring the operator's movements and analyzing the hand's trajectory. An aspect of this process was analyzing the hand trajectory to identify the most frequented areas in the workplace. These areas can then be avoided during collaborative work to minimize the risk of accidents and improve overall efficiency. Analyzing the participants' path in the environment can allow the robot to perform other tasks while waiting for the operator to complete their work. This can further increase the efficiency of the work process. In addition, the proposed experimental design is based on specific tasks that incorporate various factors to monitor collaboration. These factors include the level of concealment of tic-tac-toe pieces, pattern complexity, task sequence, the efficiency of the robot's algorithm, workspace configuration, and the operator's familiarity. We measure several variables, including time taken, idle time, frequency of idle periods, and reasons for idle states. The goal of these experiments is to manipulate these factors, collect data, and analyze collaborative performance. In the future, the goal is to utilize the results of experiments to conduct more extensive measurements and analyze collaboration by measuring the defined variables and factors.

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