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Preliminary comparison between manual assembly and intelligent human-robot collaborative assemblies in terms of quality and assembly time

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Abstract

In recent years, the use of Human-Robot Collaboration (HRC) in manufacturing systems has grown significantly, within the framework of Industry 4.0 and emerging Industry 5.0. Collaborative robots, thanks to their ability to reduce physical and mental stress of operators, enable increased productivity and quality performance. This paper analyses assembly time and quality trends as a function of assembly complexity in intelligent collaborative assembly and makes a holistic comparison between a manual assembly and two different collaborative assemblies, focusing on assembly times and in-process errors. The assembly of products with different levels of complexity is used as a case study.

Keywords: Human-Robot Collaboration; Quality Control; Assembly

1. Introduction

Collaborative robots, also known as cobots, are emerging as a promising technology in the field of robotics. These robots are designed to work alongside humans and are capable of performing a wide range of tasks, from simple pick-and-place operations to complex assembly tasks [1]. Due to their ability to work safely and efficiently alongside human workers, cobots have become increasingly popular in the manufacturing industry. In particular, they are widely used in product assembly where their use leads to increased productivity, improved quality and reduced costs [2].

Human-robot collaboration (HRC), or the collaboration between cobots and human operators, is one of the cornerstones of both Industry 4.0 and Industry 5.0, which focus on integrating digital technologies into the manufacturing process [3]. In these new industrial paradigms, there is a rising need for flexible and agile production systems that can quickly adapt to changes in demand and product design. In fact, in today's market, there is a growing demand for short runs of a wide variety of products. This is due to increasing customer demand for customisation, which is leading to an increase in the number of variants of the same product [4,5]. This approach, called mass customisation, involves the use of flexible manufacturing processes that can quickly and cost-effectively adapt to the specific needs, preferences and requirements of customers [6].

Collaborative robots are well suited to these needs, as they can be easily programmed and reconfigured to perform a wide range of tasks and can work alongside human workers to improve overall efficiency and productivity. In addition, cobots can provide real-time data and feedback that can be used to optimise production processes and improve product quality. The ability to collect data in real time also allows cobots to be integrated into the digital twin of the entire production system [7], that is essential for the continuous monitoring of production processes and machine diagnostics.

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Another key aspect in a competitive market is product quality. To achieve business success, it is essential to implement and improve quality control procedures [8]. The need for quality control in all production systems is to prevent non-conforming products from reaching the end customer or end-user [9]. Collaborative robots are increasingly used in quality control, as their ability to accurately perform repetitive and monotonous tasks can ensure the consistent production of high-quality products. Furthermore, the use of cobots can also reduce the risk of injury or strain to human workers, resulting in increased productivity and a safer working environment. As a result, the adoption of cobots for quality control is a promising solution for improving product quality and competitiveness.

In this context, the present paper proposes a preliminary investigation of productivity and quality of an intelligent collaborative assembly of electronic boards. Using a camera, the cobot is able to self-detect the components positioned within the workspace. Accordingly, it is not necessary to position the parts in specific locations, but their presence within a circumscribed area is sufficient. The main two research aims of this paper are (1) to analyse the relationship between assembly time and in-process errors with assembly complexity in the collaborative assembly of electronic boards and (2) to compare these results with two different assembly strategies (fully manual and collaborative assembly without a camera).

The remainder of the paper is organised into five sections. Section 2 describes the application of cobots in assembly processes. Section 3 analyses and model the different complexity factors in an assembly process. Section 4 introduces the case study and the experimental setup. Section 5 describes the main results of the study. Section 6 concludes the paper.

2. Human-robot collaborative assembly

Assembly processes involve the joining of several components to form a final product. These processes can be highly repetitive and require a high degree of precision, making them suitable for automation [10]. Traditional assembly processes have relied on industrial robots, which require significant safety measures such as physical barriers and cages to prevent injury to human operators. However, cobots offer a more flexible and safer option for assembly processes, which has led to a rapid increase in their use in the assembly process over the past few years.

Accordingly, one of the key benefits of collaborative robots is their ability to work in close proximity to human operators without the need for safety barriers [1]. This makes them ideal for assembly processes where HRC is required. In this context, cobots can assist with tasks such as picking and placing components, screwing and fastening, and quality control. This collaborative approach allows the entire assembly line to be optimised, with cobots taking over repetitive and time-consuming tasks, freeing up human workers to focus on more complex and creative tasks.

For instance, in the automotive industry, collaborative robots have been used to assist in the assembly of engines and transmissions [11]. These cobots work alongside human operators to assist with tasks such as tightening bolts, installing seals and fitting bearings. The use of collaborative robots has led to improvements in efficiency, quality and safety, while reducing the risk of repetitive strain injuries for human operators. Another example is the application of HRC in the electronics industry, where cobots have been used to assist in the assembly of circuit boards [12]. These cobots work alongside human operators, placing components on the board and soldering them in place. The use of cobots has led to improvements in efficiency and quality, while reducing the risk of errors and rework.

However, even in assembly processes, cobots are mainly used for pick-and-place operations. In most of today's applications, cobots pick up parts from a pre-defined position and bring them to the assembly station where the human operator assembles the various components [13]. In the present paper, a collaborative system for intelligent assembly was developed. The cobot, equipped with a camera, is able to identify the workpiece and pick it up according to a predefined sequence. This innovative system overcomes the limitations of positioning parts in a specific location for picking [13], using recognition systems that allow the different parts to be clearly distinguished.

3. Complexity of product assembly

The type of product to be manufactured, and in particular its assembly complexity, has a significant impact on the human and process performance factors that need to be monitored during the manufacturing process [14]. Using the structural complexity paradigm, each product assembly was assigned a complexity level [15]. This approach, which only considers the structural elements of the product and its assembly process, is easy to use in the early stages of product design when there is a lack of substantial or readily available operator perception data [14]. This structural complexity paradigm was originally designed for manual assembly but can be applied with a few adjustments to HRC assembly scenarios, where the cobot mainly performs organisational and logistical tasks, such as selecting the components to be assembled in a certain order and handling them to the human operators.

According to Sinha [15], assembly complexity C is defined as:

$$C = C_1 + C_2 \cdot C_3 \tag{1}$$

where C_1 , C_2 and C_3 represent parts, connections, and topological complexity, respectively.

The technological challenge of controlling and interacting with the product parts in isolated circumstances is represented by the sum of part complexity, i.e., C_1. A Design For Assembly (DFA) methodology is used to assess part complexity and to obtain a normalised handling index [16]. The physical characteristics of size, weight, handling difficulties and orientation (alpha and beta symmetry) are used to generate this value.

The sum of the complexities of the pairwise connections found in the product structure is the complexity of connections, i.e., C_2. The normalised fitting index calculated using the Lucas Method [16] can be used to measure the complexity of connections. By penalising the physical characteristics (such as part placement, part attachment, mating direction, visibility, alignment and resistance to insertion) that influence pairing difficulty, the fitting index predicts the difficulty of mating an assembly.

The average of the singular values in the product's adjacency matrix, i.e., C_3, which measures the topological complexity of the finished product's architectural pattern, increases as the system topology changes from centralised to more distributed architectures [15].

This method of defining assembly complexity was used to identify the most appropriate electronic boards for the case study, trying to select products covering a wide range of assembly complexity.

4. Human-robot collaborative assembly system

4.1. Electronic boards

In this study, six different electronic boards (ID1 - ID6) were assembled using ARDUINO UNO starter kits (ARDUINO®). The choice of assembling electronic boards was made because the kits' components can be used to create customised products with different levels of complexity. Furthermore, these boards allow real-time verification of the correct functioning of the product and, thus, of its assembly process. The selected starter kit includes the microcontroller, the components (e.g. wires, buttons, resistors etc.) and the breadboard, which serves as the basis for building the circuit. This breadboard has rows and columns of holes that conduct electricity through connectors, eliminating the need for welding. Indeed, the ARDUINO UNO Breadboard is defined as 'seamless' as the components do not need to be welded but simply inserted into the holes, Fig. 1(a) shows an example of assembled electronic board (product ID6).

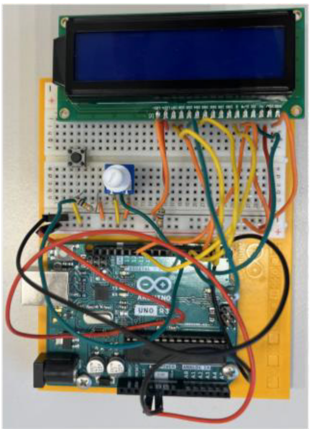
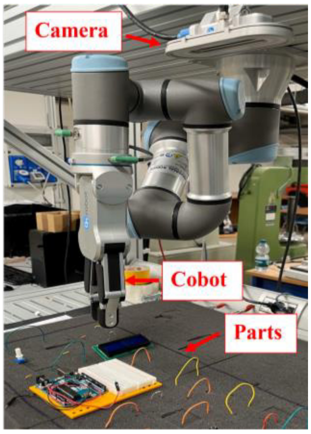
a)  b) 

Fig. 1. (a) Example of assembled electronic board (ID6); (b) HRC workstation.

In each of the six selected products, the breadboard is connected to different components in varying numbers in order to cover a wide range of assembly complexity, as above mentioned [15]. The type and quantity of components required for each of the six electronic boards are listed in Table 1. The complexity was calculated according to the criteria defined in Section 3.

Table 1. Characteristics of the six electronic boards assembled (ID 1 - ID 6).

	ID 1	ID 2	ID 3	ID 4	ID 5	ID 6
Breadboard	1	1	1	1	1	1
Long wires	-	1	2	8	9	13
Short wires	1	3	5	3	6	4
Resistors	1	1	4	6	2	2
Pushbuttons	-	2	4	-	2	1
LED	1	1	-	1	-	-
Photoresist	-	-	-	3	-	-
Potentiometer	-	-	-	-	1	1
Piezo	-	-	1	-	-	-
LCD	-	-	-	-	-	1
Battery snap	-	-	-	-	1	-
DC Motor	-	-	-	-	1	-
H-bridge	-	-	-	-	1	-
N° of parts	4	9	17	22	24	23
C_1	1.64	3.12	5.35	6.59	7.49	6.97
C_2	2.90	5.89	10.03	13.39	15.83	18.24
C_3	0.75	0.57	0.45	0.40	0.37	0.39
C	3.80	6.50	9.83	11.95	13.37	14.12

4.2. Cobot and camera vision system

The assembly of the six electronic boards was conducted using a UR3e cobot (Universal Robots™). The assembly process was facilitated by the OnRobot™ RG6 gripper, a flexible and adaptable tool designed to handle small objects. Table 2 shows the cobot and gripper parameters used during the collaborative assembly. Especially, the collaborative robot uses two types of movement: MoveJ and MoveL. The MoveJ movement moves each joint simultaneously to the desired position, resulting in a curved path for the tool. The MoveL movement moves the tool linearly between waypoints. For both movements, the identifying parameters are the speed and maximum acceleration of the joint. On the other hand, for the gripper, the main parameters are the distance between the fingers when the gripper is open and the gripping force when the gripper is closed.

Table 2. Cobot, gripper and camera parameters.

	Cobot	Gripper	Camera
MoveJ speed [°/s]	200	-	-
MoveJ acc. [°/s^2]	200	-	-
MoveL speed [mm/s]	200	-	-
MoveL acc. [mm/s^2]	200	-	-
Distance [mm]	-	25	-
Force [N]	-	80	-
Exposure [%]	-	-	14
White balance [%]	-	-	20
Light [%]	-	-	50

The cobot was equipped with OnRobot™ Eyes, an integrated vision system that enables part recognition. As shown in Fig. 2(b), the camera was positioned externally to the cobot. This was necessary due to the space limitations of the workstation, which did not allow the camera to be positioned on the cobot's wrist. For the same space reasons, and in order to limit accidental collisions between the cobot and the camera, the cobot operated at 50% speed.

The OnRobot™ Eyes system required a first stage of camera calibration. In particular, as shown in the last three rows of Table 2, it is necessary to define the exposure level, the white balance and the intensity of the light emitted by the camera. Indeed, the camera is equipped with an autonomous lighting system, which is useful to make the system independent from the lighting of the external environment. The values chosen for the experiments are the default values defined in the OnRobot™ Eyes manual.

After the calibration phase, the camera was instructed to detect the parts. The Eyes Locate function was used to define the part detection area and the detection modes. In the case study, the Location by Outline and Location by Colour and Size modes were used. The first mode allows parts to be detected based on their shape and was used for large parts such as the breadboard, LCD, battery snap and DC Moto. For all other parts, the Location by Colour and Size mode was used, where recognition is based on the colour and size of the part.

The cobot is able to pick up all the parts placed in the workstation for which the camera was instructed during the recognition phase. Using the Eyes Get Workpiece and Eyes Pick functions, the camera sends the cobot the spatial coordinates of the parts to be assembled. Then the cobot, moving with the parameters listed in Table 2 (with speeds reduced to 50%), picks up the parts identified by the camera and transports them to the human operator for assembly. When two identical parts were available for picking, the cobot always picked the leftmost part first.

4.3. Experimental procedure

The experiment consisted of two phases: the assembly phase and the quality control phase. In the assembly phase, six experienced operators were responsible for assembling the six different structures with the help of the cobot. The six structures were assembled in random order by each operator to avoid any learning effect. At the end of the assembly of each board, there was a quality control phase in which an external expert operator checked the correct functioning of the assembled board.

During the assembly phase, the UR3e assisted the operator by providing the necessary components for the electronic board assembly. The product components were arranged in random order at the workstation near the operator. Using the external camera vision system, the cobot was able to detect the parts in the work area, pick them up and deliver them to the human operator. The order in which the cobot picked up the components was predetermined according to circuit theory [17]. After each part was passed by the cobot, the human operator assembled the component on the breadboard. The cobot's functioning was always controlled by the operator, who activated it by pressing a button to perform logistical tasks. During the tests, information was collected on assembly times and process errors, i.e. errors that occurred in the assembly phase. In particular, incorrect component, unpicked component, slipped component and defective component were identified as cobot errors, while misplaced component and improperly inserted component were identified as human errors.

Despite its potential, it has to be remarked that the new collaborative camera system has some limitations. One limitation is the recognition system's dependence on surrounding light. This caused some difficulties during the part recognition phase, where the system was unable to distinguish long wires from short wires, for example. Therefore, in this first preliminary experiment, it was necessary to position the short wires to the left of the long wires, so that the camera would not confuse the components to be picked up. As it will be discussed in the next Section 5, these limitations led to an increase in in-process errors compared to different assembly strategies (fully manual and collaborative assembly without a camera).

5. Results and discussion

5.1. Experimental results

As mentioned in Section 1, the first research aim of the present paper was to study the trend of assembly times and in-process errors in relation to the complexity of assembled electronic boards. Fig. 2(a) represents the two-term power curve fitting relating assembly time and electronic board assembly complexity. This is the best fitting model compared to various models defining the relationship between assembly time and assembly complexity, considering the goodness of fit statistics and residual analysis [18]. Specifically, the form of the function is $Y = a \cdot C^b$, where Y is the response, C is the assembly complexity (see Eq. (1)), and a and b are the two regression coefficients. The results indicate that the time required for product assembly has a super-linear relationship with assembly complexity. This suggests that the cognitive effort and deliberation time required for assembly operations increases significantly as assembly complexity increases. Fig. 2 also shows the confidence and prediction intervals at 95% confidence level, which indicate that the regression lines closely follow the curvature of the points and that there are no systematic deviations from the fitted lines (see also Tables 3 and 4). It has to be noted that 95% confidence and prediction intervals are limited to zero (for both assembly times and errors) since time and errors cannot assume negative values.

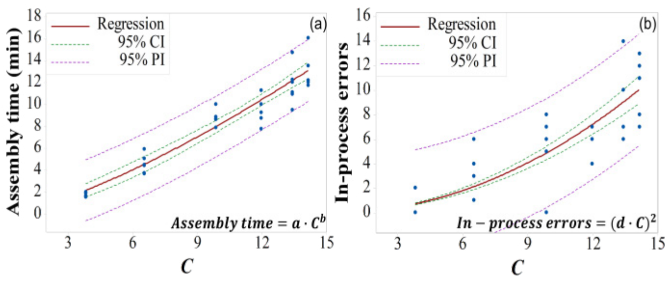


Fig. 2. Experimental values, regression curve, 95% Confidence Intervals (CI) and Prediction Intervals (PI) for (a) assembly time vs assembly complexity and (b) in-process errors vs assembly complexity.

On the other hand, Fig. 2(b) shows the relationship between in-process errors and assembly complexity. Poisson regression model was used to analyse and model this relationship. Different models for Poisson regression were compared to find the best fitting model using Akaike's Corrected Information Criterion (AICc), Bayesian Information Criterion (BIC), goodness-of-fit tests (deviance and Pearson tests), and deviance residual plots [19]. The square root link function was found to be the most appropriate one, resulting in a model in the form $Y = (d \cdot C)^2$, where Y is the response, C is the assembly complexity (see Eq. (1)), and d is the regression coefficient.

5.2. Comparison with alternative assembly strategies

The second research aim of the paper mentioned in Section 1 was to compare the above-described experiment (label as Cobot1) with two alternative strategies for assembling the six electronic boards. The first strategy involved the use of a cobot without a camera (label as Cobot2), while the second was a completely manual assembly of the electronic boards (label as Manual). It should be noted that in the alternative strategies, the six electronic boards assembled are the same, as well as the predetermined assembly sequence. The three assembly strategies are compared in terms of assembly time and in-process errors, as described in Section 5.1.

In the Cobot2 strategy, the same collaborative assembly system used for Cobot1 strategy, described in Section 4.2, was used, without the help of the camera. The board components were placed in pre-defined positions in the workstation and the cobot picked up the parts according to the pre-defined assembly sequence. The operator was always in control of the task, using a button to control the cobot. In this case, there were no space problems due to the camera, so the cobot operated at 100% speed using the parameters shown in Table 2.

On the other hand, in the Manual strategy, the operators independently selected the parts from the ARDUINO kit to be assembled on the breadboard, following the predefined order. Thus, in this experimental campaign, the operators had no help from the cobot.

The results of the comparison between the three assembly strategies in terms of assembly time and in-process errors are shown in Fig. 3.

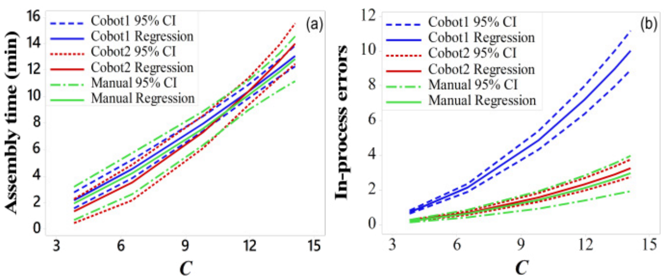


Fig. 3. Comparison between Cobot1, Cobot2 and Manual strategies on (a) assembly time and (b) in-process errors.

Regarding assembly time, it increases more than linearly with assembly complexity in all the three strategies, i.e. the form of the function is always $Y = a \cdot C^b$. Fig. 3(a) shows an overlap of the confidence intervals of the three regression curves for assembly times vs assembly complexity. Accordingly, at a 95% confidence level, no differences between the three experimental campaigns in terms of assembly times are highlighted.

Table 3 reports the main results of the regression between assembly times and in-process errors for the three assembly strategies. Looking at the last columns of Table 3, there is numerical evidence that the confidence intervals of the parameters overlap at the 95% confidence level.

Table 3. Main outputs from non-linear regression for assembly time vs assembly complexity.

Strategy	a	SE(a)	b	SE(b)	95% CI (a)	95% CI (b)
Cobot1	0.344	0.099	1.373	0.115	(0.185,0.591)	(1.157,1.619)
Cobot2	0.123	0.085	1.787	0.272	(0.020,0.448)	(1.275,2.490)
Manual	0.279	0.190	1.447	0.270	(0.052,0.915)	(0.970,2.105)

On the other hand, as far as in-process errors are concerned, in all three assembly strategies the errors follow the same trend as a function of assembly complexity, i.e. a Poisson model with a square root link function $Y = (d \cdot C)^2$. However, it can be seen at the 95% confidence level that the Cobot1 strategy has a significantly higher level of in-process errors than the Cobot 2 and Manual strategies. Figure 3(b) shows that there is no overlap between the 95% confidence intervals of the Cobot1 strategy and those of the Cobot2 and Manual strategies. Table 4 reports the same results from a numerical point of view.

Table 4. Main outputs from Poisson regression for in-process errors vs assembly complexity.

	d	SE(d)	95% CI (d)
Cobot1	0.224	0.006	(0.211,0.237)
Cobot2	0.128	0.005	(0.117,0.137)
Manual	0.122	0.010	(0.099,0.141)

This significant difference in in-process errors is due to a still unstable camera vision system, which does not always allow for the correct recognition of the parts to be assembled that the cobot must pick up. On the contrary, in the Manual and Cobot2 strategies, the operator and the cobot typically picked up the correct parts as they were placed in specific positions. Therefore, by refining the vision system, it will conceivably be possible to reduce these errors in part recognition.

6. Conclusions and future works

Collaborative robots have become popular in assembly processes because they can work alongside human workers to perform repetitive tasks without interruption or fatigue, increasing the efficiency of the production process. They also create a safer working environment by performing hazardous tasks that could put human workers at risk.

This paper investigates the effect of assembly complexity on assembly time and in-process errors in collaborative assembly. Specifically, an experimental campaign was conducted on the collaborative assembly of six different electronic boards. The results showed that the time required to assemble an electronic board has a super-linear relationship with its assembly complexity. With regard to in-process errors, experimental results showed that as assembly complexity increases, errors tend to occur more frequently, and that this relationship follows a non-linear pattern.

The results of the described experimental campaign (called Cobot1) were compared with that of two alternative assembly strategies (called Cobot2 and Manual). Cobot2 strategy has the same configuration as Cobot1, but without the use of the camera (parts are picked up at specific positions), while Manual strategy involves a completely manual assembly without cobot support. The results showed that assembly time increased with increasing complexity, with the same type of power-law trend for all three experiments, and that there was no significant difference in assembly time between the three strategies at a 95% confidence level. Even for in-process errors, these increased super-linearly with increasing assembly complexity. However, the cobot with the camera (Cobot1) had a significantly higher level of in-process errors than the two alternative strategies due to the high number of parts not detected by the camera.

In conclusion, the Cobot1 vision system provides a powerful solution for the assembly process, eliminating the need to retool the workstation each time and minimising the time and effort required for part selection (as with the Cobot2 and Manual strategies). This is particularly beneficial for components that are very similar and require customisation for a large number of variants. However, this study has identified a limitation of the system, i.e. an immature camera vision system. As a result, the system struggles to clearly distinguish between different parts, particularly small components such as cables, leading to a higher average level of in-process errors compared to the Cobot2 and Manual strategies. Thus, future research will focus on refining the camera vision system and evaluating additional parameters such as the stress perceived by the human operator. With these improvements, the Cobot1 strategy has the potential to improve the assembly process, increasing efficiency and quality.

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