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Complexity based investigation in collaborative assembly scenarios via non intrusive techniques

Sotirios Panagou[a]*, Monica Sileo[a], Konstantinos Papoutsakis[b], Fabio Fruggiero[a], Ammar Qammaz[b], Antonis Argyros[b]

[a] *School of Engineering, University of Basilicata, 85100, Potenza, Italy*
[b] *Computational Vision and Robotics Laboratory, Institute of Computer Science, Foundation for Research and Technology – Hellas, 70013, Heraklion, Greece*

Abstract

Human and robot collaboration in assembly tasks is an integral part in modern manufactories. Robots provide advantages in both process and productivity with their repeatability and usability in different tasks, while human operators provide flexibility and can act as safeguards. However, process complexity increases which can lower the overall quality. Increased complexity can negatively influence decision making due to cognitive load on human operators, which can lead to lower quality, be it product, process or human work. Moreover, it can lead to safety risks, human-system error and accidents. In this work, we present the preliminary results on an experiment performed with student-participants, based on an assembly task. The experiment was set up to emulate an industrial assembly, and data collection was performed through qualitative and non-intrusive quantitative methods. Questionnaires were used to assess perceptual task complexity and cognitive load, while a stereo camera provided recordings for after-task analysis on process errors and human work quality based on a 3D skeleton-based human pose estimation and tracking method. The aim of the study is to investigate causes of errors and implications on quality. Future direction of the work is discussed.

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Keywords: collaboration; assembly task; complexity; cognitive load; human pose estimation and tracking.

* Corresponding author. Tel.: +39 0971 205 196; fax: +39 0971 205 160.
E-mail address: sotirios.panagou@unibas.it

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1. Introduction and Background

Human-robot collaboration (HRC) is a growing trend in manufacturing and assembly contexts. It is a form of interaction where humans and robots work in close physical proximity without barriers [1]. In a collaborative assembly, humans and robots work together to perform the same task, sharing the same workspace and task resources. In this context, the collaborative task benefits from the repeatability, usability and accuracy of the robots, and the flexibility, problem-solving and versatility of humans [2]. The expectations from HRC are higher productivity and product quality. Due to the physical interaction between them, Human Factors and Ergonomics [3] can contribute to the overall success of collaboration due to the (i) importance of human safety and (ii) quality of collaboration, be it product, process or human work quality. In HRC, the use of collaborative robotics (cobots) increases the complexity of the task process as well as the complexity of process information, task management and interaction. Human operators need to interact with cobots, while performing their tasks and be aware of the process steps and safety procedures. As such, task complexity plays an important role in collaboration and can be divided into the static and dynamic subcategories. Static complexity does not change during the task (i.e. task variants, instructions, workplace layout and environment). Dynamic complexity is dependent on the variables of the task, resources, time, probable events (i.e. mishandling, downtime, or mechanical failure) and is also subjective to the operator perception [4]. The amount of information and task parameters the operator needs to process, increases the complexity and in turn increases the probability of error [5]. Due to the complexity and increased error probability, human safety should be at the forefront of design with the aim of avoiding accidents and potential injuries.

Human safety can be divided into two subcategories: the actual safety of the human operator and the humans' perceptual safety during the task. In a collaborative assembly, the challenges for safe interaction refer to the safety standards and the collaborative operating modes [6]. One important safety aspect in HRC is collision avoidance due to the close and physical interaction between humans and the cobot. Collision avoidance techniques are boosted through (cyber physical-) sensors and machine vision [7]. Moreover, sensors and video-capture methods can be used to observe human operators and provide information during task and process, and for error analysis [8]. A classification of aims, systems, devices and actions for safety in industrial collaborative environments can be seen in Robla-Gómez et al., [9]. Perceived safety is subjective to the individual human operator and refers to the feeling of safety [10] which depends on the mental stress or anxiety due to collaboration with cobots [6] and stress or discomfort induced by the cobot's function and characteristics [11]. Lack of perceived safety can be manifested through distrust and fear of robots, stress or anxiety during the collaboration and surprise due to the robot's appearance, action or movement. A more detailed report on perceived safety in HRI can be found in Rubagotti et al. [12].

Each operator reacts differently to a situation, depending on their characteristics and the perception – reaction loop. The information received during a task, managing the task and collaboration, mental and psychological reactions to events could impact their stress levels, cognitive load and reactions, affecting their decision-making skills which can lead to human-system error [13, 14]. In that regard, supporting human operators in collaborative tasks should be a priority in order to minimize uncertainty and probability of error. Investigating the root causes of stress and error in HRC can improve knowledge on how to support human operators, through developing supporting systems and assisting them by positively influencing their perceptual safety and complexity through training or other means. Performance and product quality are some of the measures used for effectiveness and successful operations [15]. However, due to the robot presence and planned collaboration, human operators face the challenge to keep their performance high whilst also keeping product quality high. Perception plays a significant role in their reactions. Perceptual cognitive load, safety and task complexity affect performance, product quality as well as process and human work quality.

In this work, we present the preliminary results of an experimental test regarding a collaborative assembly task. The experimental design follows the design and logic presented by Fournier et al., [16], and the goal of this work is to investigate and assess the human operators' perceptual complexity and cognitive load, and investigate the impact on decision making and quality through questionnaire and interviews to understand the root causes of errors. The task was designed with an industrial assembly line as a guide and as such, only non-intrusive quantitative methodologies and tools were used. Questionnaires were used to capture the participants' perception of the task and collaboration (after the experiment). In the next section, the experiment design, methodologies and tools, and general information on participants are discussed. Next, the preliminary results are shown with context and error analysis. Finally, conclusory remarks are presented.

2. Experimental methodology

In this section the experimental set-up and methodologies used for the first group of participants are presented. The participants that volunteered were separated into groups for safety and health (due to COVID-19) reasons. In the first group, for which results are presented below, 12 engineering students (bachelor and master level) were selected, with a mean average age of 24 years, and no prior experience with robots. As the students will perform two test task phases, the fact that they possess no experience working with robots was considered important for this experiment as it can provide an insight at basic errors and their root cause. In the second test phase, as the participants will be familiarized with the task and collaboration with the robot, it can allow a look on which errors from the first task were corrected and which were not. This could allow an investigation on which errors could be due to system processes or the need for operators to better understand what is asked. In this case, those errors can be analysed to investigate which areas need to be supported, better designed or explained, or in which areas participants (and operators) need to be trained. The results will be supported by use of questionnaires and an interview.

2.1 Set-up and equipment

The experimental study is based on collaborative assembly. During the assembly, the participants need to perform two tasks; the main task involving the collaboration, and a secondary task which is performed manually but is considered part of the collaborative assembly as the components assembled here are essential for the final product (e.g. in an industrial assembly, small components are picked and handled manually before used in the main assembly). The main task involves product assembly through collaboration with a cobot. The cobot picks and delivers the components to the participants, who then have to retrieve the component from the cobot's gripper without delay (no downtime rule) and assemble the main product. During the time where the robot moves to pick and deliver the components, the participants need to perform the secondary task which involves assembling a different product manually from shop-orders. In the secondary tasks (manual), the participants need to pick the components manually, following the guidelines set beforehand. In this task the complexity increases, as it involves assembly of products using components of different colors. When the cobot delivered the final component, the participants were given enough time to complete the main product and one final manual assembly, before the overall task was considered finished. The participants were given informational text and the guidelines on how to complete the products and process, along with a presentation of the objective of the study and a video showcasing the task. At this point, the students had to confirm their availability and give their consent, otherwise they could withdraw.

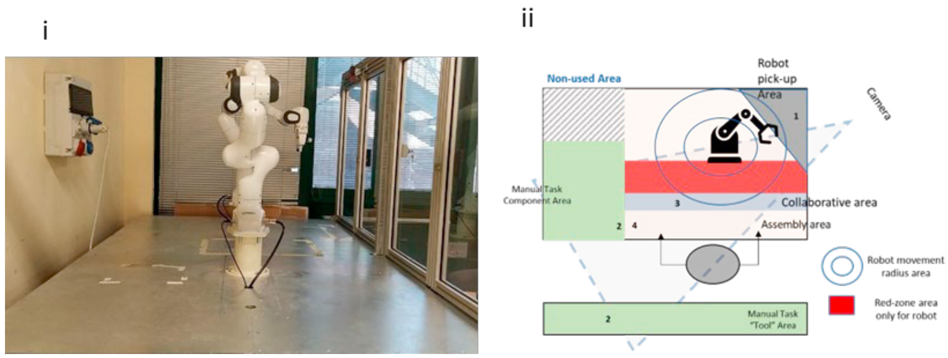

Fig. 1. Test area (left) and schematic representation of task areas (right). Numbers indicate the respective task areas during task procedure. Video was placed in a diagonal position for better coverage and depth.

The area where the tests took place can be seen in figure 1. The Franka Emika Panda robot arm was used for the collaboration due to its interface and adaptability for task design. Moreover, it provides flexibility for grasping objects of various shapes and size, and stable delivery of said objects through a predefined path to its target [17], by using a gripper characterized by parallel fingers, that can exert a maximum force of 100 N. The Franka Emika Panda collaborative robot has 7 degrees of freedom (joints) and it is equipped with torque sensors in all 7 axes, which allow the robot to perform sensitive manipulation. Moreover, it has an external activation device, that can be used to stop its movement, at any time, during the execution. The robot can be programmed by a web interface (Desk). This interface contains modular robotics program, which can be seen as partial steps of a robotic task.

The cobot also has a user interface on the arm for guiding and operating through a personal computer. This allows the user ease of interaction, which is beneficial for HRC and studies on user experience; namely the experience evoked while humans interact with technology [18] and mixed reality [19]. The robot motion has been programmed by setting the grasping pose (by recording configuration on robot joints) for each components of the main product, placed in the robot pick-up area in a fixed position, and the pose in the collaborative area to deliver the component. For each joint, the control system plans a trajectory between two configurations.

To pick up the object, the participants needed to use the button on the upper part of the robot arm, so that the gripper would release the component and the task can continue. Those actions must be performed when the robot is out of its "executing task" mode. The participants can be aware of the robot's mode by checking the lights on the robots base that indicate its status. Interaction must happen under blue light status and there must not be any interaction when the status is green ("executing task"). As can be seen in figure 1, the test area was divided into separate sub-areas. The participant could only assembly in the dedicated assembly area and interact with the robot in the dedicated collaborative area. Movements towards the main robot parts was designed as a red zone, for collision avoidance and safety reasons; to ensure safety in case a participant moved into the red zone two measures were put in place: (i) the researchers could stop the cobot manually in case of safety risk and red zone overlap, and (ii) a collision avoidance system. The components for the manual assembly, were placed in the left side in an easily accessible area where the participants could pick-up the components comfortably. A designated area for components (assigned as tools) were also placed behind the participants, where they had to turn to pick the components, following the procedure dictated by the experiment instructions which they had to read.

2.2 Task process and data collection

Table 1. General description of experimental task steps. Numbers (1), (2) and (4), indicate the areas the participant and robot performed the tasks (figure 1 areas).

Time (sec)	Action – Participant	Action - Robot
0-0:14	Begin manual assembly (2)	Pick component and move towards participant (1)
0:15-0:17	Pick component from robot (3)	Deliver component to participant (3)
0:18-0:25	Assembly steps (4)	Move to component area (1)
0:26-0:34	Assembly steps (4)	Pick component and move towards participant (1)
0:35-0:37	Pick component from robot (3)	Deliver component to participant (3)

The general process of the task can be seen on table 1 and the general-purpose flow on figure 2. At the end of the task, a visual inspection on the products (collaborative and manual) was performed for quality purposes (product quality). After the task the participants were asked to complete two questionnaires regarding perceptual task complexity and perceptual cognitive load. For the task complexity, the questionnaire was formed based on the CXI index as shown in Mattson et al. [20]. For the first test phase, the gas-tank questionnaire for cognitive load was used [21], along with some general questions on mental, physical and temporal demand based on the NASA-TLX [22] to familiarize the participants on the procedure for the second test phase. After the participants finished the questionnaires, a small interview was performed (5 questions), with questions on their view on the experiment, feelings during the task and their performance.

Fig. 2. Sample process of HRC experimental task steps.

The experiment was recorded using a Stereo Labs™ ZED-2 stereo camera The purpose of video recordings is to identify errors and assess human work quality during the process. The errors can then be correlated, with the participants' assistance, with an action or feeling (stress, uncomfortable), or other reasons during the task process. Moreover, each video will then be analyzed in order to estimate and track, in real-time, the 3D human body motion using the MocapNET2 method based on the monocular 2D color (RGB) images of the input video [23].

Thus, given a video comprising a sequence of N images that shows the process, we employ state-of-the-art deep-learning-based methods for the estimation of the 3D skeleton-based pose of the human body per image. Specifically, we use the efficient OpenPose method [24] to obtain a set of 2D image coordinates (x,y), that is the locations of 25 skeletal body joints according to the BODY25 pose output model. The MocapNet2 approach [25] relies on the estimations of the 2D body motion to drive ensembles of Deep Neural Networks that are able to efficiently regress a view-invariant skeleton-based body pose in 3D space. Moreover, the hierarchy of the 3D skeletal body model is split into the upper and the lower body parts that are estimated independently, in order to tackle cases where the presence of severe and possibly long-term occlusions of the human body deteriorates the quality of estimation and tracking of the human poses. The output of the MocapNet2 method is a Biovision Hierarchy (BVH) character animation file format [20] representing the estimated 3D human motion observed in the input image sequence. For each input image, the estimated 3D human pose comprises the 3D location and orientation of 25 main body joints (including the base/middle/upper spine, neck, head and both left and right shoulder, elbow, wrist, hand, tip of hand, thumb, hip, knee, ankle, and foot).

This rich information can be used to estimate the human body orientation through skeletal tracking, to perform physical (posture-based) ergonomics analysis, estimate reactions and analyze further considerations related to human motion and physical condition. This can also provide information and data for risk assessment and quality purposes, and along with the answers operators can give it can allow in improving task and process design.

3. Initial results in HRC complexity based investigation

Due to the fixed scheduling and the no downtime rule for the robot, the average time of collaborative assembly was 3 minutes and 10 seconds, while the participants were given enough time to complete one final manual assembly step (average of 8 seconds more). With the process finished, the quality of the product was rated by the following: (i) product is finished and (ii) assembly process was correct with no errors and no mismatch (figure 3). From the 12 participants, only 4 managed to finish the collaborative assembly product correctly, while 2 did not finish the process as they caused a robot malfunction (they exerted excessive force on the button and so the collision and safety system stopped the task execution). The rest did finish the product, however there was a mismatch or failure to follow the assembly instructions; final product was not the same as the one shown (wrong orientation of coloured blocks).

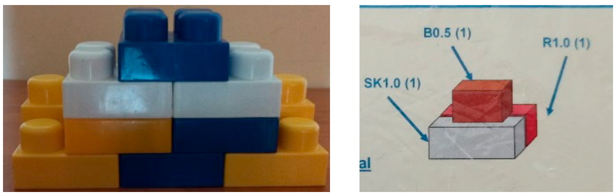

Fig. 3. On the left, the collaborative assembly product. On the right, sample of the shop orders given to the participants. The total amount of shop orders was 6.

For the manual assembly, the total amount of products to be assembled were 24. A minimum acceptable amount of 12 finished products was set, according to percentile acceptance value based on experimental values and consensus between research and industrial requirements, as product quality is relevant with process quality and market acceptance rate. Only two participants (ID's 1 and 3) managed to complete more than the minimum acceptable number (14 and 18 respectively). One participant did not follow the shop orders and did not finish any acceptable product. From the preliminary analysis of product inspection and video analysis, the process and product errors were found and recorded in a database (table 2). The collected questionnaires were analysed and recorded into the database and the internal consistency of the questionnaires was confirmed (complexity questionnaire p-value<0.01

and for cognitive load, Bartlett Test chi-square of 78 and p-value<0.01).

Table 2. Results obtained through the experimental analysis: completed collaborative and manual products, process and product errors, cognitive load from NASA-TLX (gas-tank questionnaire answer was used for the participants that did not complete the NASA-TLX and is marked as such), and average complexity index CXI over task areas.

	Collaborative	Manual Assembly						
ID	Col.A	Completed	Errors	Process Errors	Total	CL – NASA-TLX	Complexity	
1	*Finished*	14	2	2	4	45	Product	2.67
2	*Not finished*	11	1	2	3	90 (Gas-Tank)	Work	3.41
3	*Finished*	18	2	0	2	75 (Gas-Tank)	Station	2.33
4	*Not Finished*	2	1	10	11	41	Collaboration	1.6
5	*Partially*	8	0	3	3	42	Instructions	2.05
6	*Partially*	7	5	3	8	42	General	2.2
7	*Partially*	6	1	8	9	75 (Gas-Tank)	**Final CXI**	**3.23**
8	*Finished*	7	6	0	9	50 (Gas-Tank)		
9	*Not finished*	8	2	3	5	67		
10	*Partially*	0		3	3	56		
11	*Partially*	5	1	7	8	75 (Gas-Tank)		
12	*Finished*	9	3	2	5	67		

Qualitative and quantitative data were collected from the questionnaires filled by the students. Through the CXI method, the final complexity (perceptual) was calculated (table 3). From the analysis, the area where the students believed to be more complex was the work-related content (3.4). This was mostly due to inexperience with the task and the high temporal demand of the experiment. The lowest complex area was the collaboration area (1.6), were the students stated (questionnaire and interview) that the robot's movement and handling, and the interaction were well designed, while also that the collaboration was not stressful. From an interview conducted with all the participants after they performed their task, the main two root causes of errors in manual or collaborative assembly and process were the following: (i) the no downtime rule for the robot (picking components from cobot without delay for the cobot) caused stress as they were not sure of the robot's position (due to additional task of turning around and picking components) which impacted process management, which in turn caused (ii) high mental demand as they needed to decide in short time how to proceed and which components to pick.

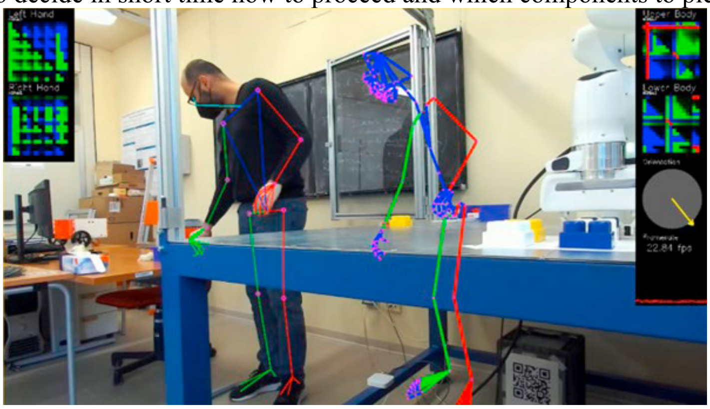

Fig. 4. Example of posture not following the instructions for correct procedure in picking the "tool" component seen through the MocapNET2. The estimated 3D skeletal body pose is overlaid to the actual locations of the human body, while the full 3D skeletal model is rendered using a spatial offset in the image (for viewer's discretion).

High mental and temporal demand of the task caused the participants to not follow the instructions on how to pick up the “tool” components from the designated area behind their workspace. Video recordings also allowed analysis on the participants task management and posture; analysis revealed that participants did not follow the instructions on material handling and picking in their entirety due to being stressed that they won’t be able to finalize their tasks (e.g., figure 4). This partial fulfilment of the instructions resulted in errors when returning to the assembly area, such as components falling or rushing to interact with the robot arm when the robot was still moving.

4. Conclusions

Human robot collaboration is considered beneficial in manufacturing, due to the combination of robot’s repeatability and usability, and the flexibility of human operators. However, due to the increased complexity, it is essential to know how human operators and human factors and ergonomics are affected. This in turn can prove crucial in increasing or maintaining productivity and overall quality of product, process, and human work. In this work, we present a preliminary experiment on human robot collaboration with the intention of investigating the factors that lead to errors. Perceptual task complexity and cognitive load are investigated by questionnaires, to understand the demand placed on human operators by an assembly process, where they need to collaborate with a robot and fulfill secondary tasks. The analysis showed an overall complexity index CXI of 3.23 and an average 51.42 NASA-TLX score. Video analysis showed errors in assembly (wrong assembly steps) and process (mishandling components and collaborative process). Moreover, it reported that no participant followed the instructions on how to pick the components from the tool area correctly. The participants revealed in a short interview that the two main reasons for their performance was the stress of not knowing where the robot is, and the mental capacity needed to make the decision on how to proceed during the process. This study provides indications and several contributions on HRC research, design, and error analysis. The method described above is used for the continuation of the experiment with the next groups of participants and also for the next phase of the experiment with the first group. The future direction of the research is to extend the experiment with cognitive human factors as focus, and for real time industrial monitoring in collaborative assembly workplaces. From a managerial perspective, the results of such a test can be used for tasking purposes and workplace safety and design aiming in improved quality and reliability.

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