Creating a Framework for a User-Friendly Cobot Failure Management in Human-Robot Collaboration

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ABSTRACT

Solving failures is part of our private and work lives. With the ongoing changes in the industrial production setting, we have to deal with new failure originators: collaborative robots (cobots). Failure communication and subsequent recovery are essential to improve performance and restore trust after cobot failures. Therefore, we propose a framework for cobot failure management (FCFM) to support failure communication and solving in the production context. In a study with workers (N = 35), we investigate the impact of the helpfulness of the FCFM for workers. The first preliminary results demonstrate that the FCFM helps facilitate failure communication and rectification.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in collaborative and social computing**; **Empirical studies in HCI**.

KEYWORDS

Cobot, Human-Cobot-Interaction, Cobot Failure, Failure Management

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1 INTRODUCTION

Integrating collaborative robots (cobots) into production processes has revolutionized manufacturing operations in today's dynamic and technologically advanced industrial landscape. Cobots combine the safety standards for collaborative work with humans and the possibility of diverse and flexible usage through simple programming. Unlike traditional production robots, cobots used cooperatively or collaboratively are not fenced off. This collaborative aspect of cobots offers a significant advantage in addressing the impending shortage of skilled workers by facilitating teams comprising humans and cobots while enhancing ergonomic working conditions to prevent potential long-term health issues [26]. Cobots promise to open new avenues for increased productivity, efficiency, and flexibility within production settings. However, the interaction between humans and cobots has its challenges. One critical aspect that demands thorough attention is the communication and management of cobot failures that may occur during collaborative tasks. These failures can result from various factors, including mechanical malfunctions, programming errors, and unforeseen interactions with the environment [13]. Failures in an industrial setting can have profoundly negative impacts on operators and manufacturers, leading to consequential effects such as production stoppages, which are always a matter of cost. Therefore, investigating tools and strategies to mitigate the effects of cobot failures is not only directly linked to improving the well-being of operators but also crucial for the efficiency and competitiveness of companies. Effectively addressing these failures necessitates a well-structured communication strategy that enables seamless information exchange between humans and cobots. Failures are inevitable, and research has shown that they can elicit negative emotions such as frustration [27], reduce the willingness to use robots [5], and lose trust in automation (e.g., [6, 10, 11]). Given these challenges, the fundamental question arises:

How can seamless communication and management be achieved when cobots encounter failures?

This paper proposes a *framework for cobot failure management* (FCFM) designed to help manage cobot failures in an industrial setting. The FCFM addresses three phases of failure management: 1. the detection of the failure, 2. the communication of the failure, and 3. the rectification of the failure. For each phase, the specific strategies will be systematically explained. In addition, a user study involving 35 workers from a robot manufacturing environment explores the FCFM. The preliminary results show that the FCFM is perceived positively.

2 DESIGN OF A FRAMEWORK FOR COBOT FAILURE MANAGEMENT

2.1 Theoretical Background

Honig and Oron-Gilad [13] propose an information processing model called *Robot Failure Human Information Processing* (RF-HIP). It is a modification of the Communication-Human Information Processing [28], which is a model for the human processing of warnings. The RF-HIP model focuses on the person's processing of failures and the influence of context factors on the *person*'s perception. RF-HIP differentiates three parts regarding a robotic failure: the communication, the perception and comprehension of failures, and the solving of failures [13]. The following FCFM adopts the three-part division of the RF-HIP and adapts it to the specific requirements of cobots and their usage in the industrial setting: firstly, the *detection* of failures, secondly, the *communication* of failures, and thirdly, the *rectification* of failures. Additionally, there is a shift in perspective, with the cobot's viewpoint taking precedence. This shift aligns with the FCFM's objective to enable the detection, communication, and rectification of *cobot* failures. Furthermore, the FCFM aims for a sustained impact, necessitating the capability to store failure information for all FCFM components in a database and access it when needed.

Finally, we are interested in how control over failure management should be shared between cobots and humans in the three phases. This aims to answer the question of who should be proactive or reactive during the interaction. Existing studies in human-robot interaction (HRI) suggest that proactive behavior in social robots can positively influence users' perceptions [2, 18, 24, 29]. Typically, proactivity is categorized into three interaction dimensions: the robot's approach to humans [4, 7, 16], collaborative task allocation based on user intent [1, 14, 22], and proactive assistance offered to the user [9, 23, 24]. This paper focuses on existing theoretical concepts for offering proactive assistance, as we deem them to be adaptable for effective failure management. In this regard, proactive behavior often correlates with the level of autonomy displayed by the robot in mixed-initiative interactions with social robots [3, 19, 24]. The concept of levels of autonomy, initially developed for autonomous systems, encompasses ten levels delineating the system's control extent. Lower levels grant users more decision-making authority, while higher levels involve greater system responsibility [3]. Beer et al. [3] introduced a framework in HRI based on these autonomy levels, aiming to guide robot autonomy design and emphasize conveying the robot's autonomy during interaction. For instance, Peng et al. [24] described proactive interaction at three autonomy levels: low, medium, and high. At the low level, the robot primarily reacts, while at the medium level, proactive behavior is initiated after user confirmation of needing assistance. At the highest level, the robot proactively offers recommendations without explicit user confirmation. In various user studies, Kraus et al. [17, 18, 20, 21] found the selection of an adequate level of proactivity to be highly context- and user-dependent, showing different outcomes on user experience and system trustworthiness. Currently, no evaluation of varying levels of proactivity exists in the context of failure management. Therefore, we deem it necessary to extensively study this aspect in our forthcoming works.

2.2 Framework for Cobot Failure Management

An overview of the FCFM and its three phases are given in Table 1. *Failure Detection* of the FCFM enables both the cobot and the worker to detect cobot failures. It facilitates proactive detection by the cobot and reactive detection by the worker. Proactive detection can involve sensor data from the cobot, like the positions and rotations of its actuators and the status of its end-effectors. Research indicates that humans react socially to robot failures [8, 25]. Hence, leveraging the worker's facial expressions or other social signals is conceivable, albeit requiring careful consideration within a work context, prioritizing the worker's preferences. Depending on the cobot's application, specific tasks, and surroundings, additional sources of information, such as the weight of the assembly piece, the distance between the cobot and the worker, or lighting conditions, can be integrated for more comprehensive failure detection. In *Failure Communication*, there exists a distinction between proactive and reactive communication, where proactive can be translated as communication from the cobot to the human and reactive vice versa. Communication can entail and combine different modalities, such as light, vibration, and audio signals. While those signals suffice for the communication of the *existence* of a failure, they cannot be used for the *details* of the failure's circumstances. Thus, those modalities must be combined with a communication modality that allows a richer transfer of information, which will be the centerpiece of the FCFM: a graphical interface that provides the worker with further information about the failure. In addition to more detailed information, a graphical interface allows for a prolonged presentation of information, allowing the worker to obtain information repeatedly if needed. *Failure Rectification* is the last phase covered by the FCFM. It entails the active process of resolving the failure, which the cobot can do (proactively) or the worker (reactively), depending on the specifics of the failure. The cause of a failure must not be definite. Thus, the database of the failure must contain the possibility of different rectification strategies and display them to the worker. Overall, the FCFM aims to enable the worker to manage cobot failures. A small user study was conducted to investigate the FCFM empirically.

3 USER STUDY AND PRELIMINARY RESULTS

In the following, we describe the study design. Subsequently, we present the preliminary results on the perception of the FCFM.

Failure Phases	*Cobot's Level of Control*	*Implementation in User Study*	
		Cobot	**Worker**
Failure Detection	Proactive	implied by the cobot's communication	—
	Reactive	—	implied by communication of failure
Failure Communication	Proactive	red light and pop-up window in interface	—
	Reactive	—	report the failure on the interface
Failure Rectification	Proactive	recalibration (F_{align})	—
	Reactive	—	placing nut (F_{nut})

Table 1: Overview of the different phases of the FCFM.

Figure 1: Collaboration between a person and the LBR iisy.

3.1 Methodology

3.1.1 Participants. The participants were apprentices at KUKA in Augsburg. A total of 35 people participated in the study. Six were female and 29 were male. The gender imbalance represents the current distribution in the field and is not based on the preferences of the study design. Two participants had a physical disability. The age distribution was as follows: 2 being 16-17, 23 in the range of 18-19, and 9 in the range of 20-29. In the case of participants younger than 18, the consent of a legal guardian was obtained. Participants are doing their training in the areas of industrial mechanics, mechatronics, electronics, and commercial activities.

3.1.2 Setup and Procedure. The cobot LBR iisy 3 R760 was used in the study. It is a collaborative robot arm by KUKA with six joints. A parallel gripper by Zimmer was mounted onto the cobot's flange. Beneath the flange, an LED ring is built in. The participant stood in front of a perforated wall while the cobot was on the other side of it (see Figure 1). On the cobot's side, four nuts are laid in designated locations. On the participant's side, screws and washers were ready in a box left to the perforated wall, as well as four angle connectors. On the right side of the perforated wall facing the participant was the graphical interface on a tablet and, next to it, a digital timer.

After consenting to participate in the study voluntarily, participants were presented with a cover story: they should imagine that they worked at a production site and had to assemble a "workpiece" with the cobot. Their sole possibility to communicate with the cobot was via the graphical interface. Participants were not told that they would encounter cobot failures. There were four sessions, each entailing the assembly of one workpiece. A workpiece consisted of four angles mounted onto the panel. Each session began with the cobot gripping a nut and moving its body such that the gripped nut aligned with a hole in the perforated wall. The participant was instructed to take a screw, insert it into an angle connector with a washer in-between the head of the screw and the angle connector and tighten the screw. After participants tightened the screw, the cobot opened its gripper and moved to grip the next nut. In sessions 2 and 4 each, a failure occurred. Those were preprogrammed. Two different failures were tested for. The first failure (F_{nut}) entailed the cobot opening its gripper after aligning the nut with a hole in the perforated wall, but before the participant was able to fasten the angle connector. The second failure (F_{align}) involved the cobot aligning inaccurately with a hole in the perforated wall, preventing the participant from attaching the angle connector to the wall.

3.1.3 Prototypical Implementation of the FCFM. The prototype of the FCFM implemented in this study focuses on *communication* and *rectification.* As can be seen in Table 1, the *detection* is implied by the communication. For communicating failures, two different modalities were used: light and a graphical interface. In the ordinary collaboration with no failure, the LED ring of the cobot was green, which changed to red in case a failure occurred. In the *reactive* condition, the change of light corresponded temporally with pressing the button "report failure" on the interface. Here, the failure communication strategy corresponds to the lowest level of proactive dialogue, "None," as described in [18] where it is optional for the user to report a failure. For the *proactive* condition, the change of color co-occurred immediately with the occurrence of the failure independent of the participant's awareness of the failure. Additionally, in the proactive communication strategy, the interface's regular screen was adapted in the following ways: a red window appeared reading "A failure has occurred! Unless you click Next, you will be automatically redirected to the failure detection in 15 seconds." Accordingly, the screen changed to the first step of rectifying the failure process after 15 seconds. Here, the failure communication strategy refers to the highest proactive dialogue act, "Intervention," in which the user has no option other than to follow through with the guidance provided by the interface.

For *rectification*, instructions and information about the cause of the failure were given in the graphical interface. F_{nut} had to be resolved by the participant. Thus, the cobot's level of control during the rectification for this failure is *reactive.* On the other hand, for F_{align} the cobot could resolve the failure independently by recalibrating. Here, the cobot *proactively* resolved the failure.

3.1.4 Evaluation Methods. In this study design, both quantitative and qualitative methods were combined. For measuring changes in trust, the *Short Learned Trust in Automation Scale* (LETRAS-G) was used. It is a German scale derived from the *Trust in Automation* scale by Jian et al. [15]. For measuring frustration, the frustration scale of the NASA-TLX was used [12]. The central part of the qualitative methods consists of the non-participant observation of the interaction between the participants and the holistic cobot application, with a particular focus on the FCFM and the semi-standardized interview at the end. An observation protocol was drafted in advance to capture predefined focal points in a structured and standardized manner. The design of the interview guide was based on the structure of the interview template by [5] for researching trust in HRI but was extended with specific questions about the perception of failures in this study. Almost exclusively open questions were formulated to encourage the participants to express their perceptions.

3.2 Preliminary Results

The following preliminary results focus on the FCFM and its appreciation by the participants based on open questions asked in the interview after the interaction with the cobot. An extensive analysis of the conditions will be done in the future.

Participants were asked Q_1: *How do you rate the interaction with the tablet as a troubleshooting tool?* 76.5 % of the answers were positive. The FCFM was perceived as helpful, easy to use, and straightforward and that it could rectify failures independently. 5.9 % of the answers can be classified as neutral, and 14.7 % were negative. It was rightly emphasized here that a graphical interface can be problematic if workers wear gloves or when there is much dust in the production hall. An additional answer (corresponding to 2.9 %) did not fall into this scheme. A more specific question followed Q_2: *How helpful did you find the (failure management) system during troubleshooting?* 51,6 % of the participants found the graphical interface very helpful, while 35.5 % found it helpful. Participants viewed the instructions during the troubleshooting to be helpful: *[P28]: 'very helpful without this I would not have known how to continue,[it] would have taken much longer'* The remaining 9.6 % did not find the interface helpful. Here, further analysis yielded no specific insights. The last question regarding the FCFM reads Q_3: *Did you have the impression that the system actively helped you with troubleshooting?*. 92.6 % of the participants affirmed, and the remaining negated. The participants emphasized again that they would only have been able to rectify the failure with the FCFM. On the other hand, it was noted that the failure had to be rectified independently. The light modality of the FCFM was perceived by 85.7 % of the participants. A correct attribution between the colors green and red and their meaning was given by 33.3 % of the participants. The observations during the failure reveal that a great majority of the participants (78.6 %) did not independently use the graphical interface to rectify the failure. After a reference to the interface by a researcher, every participant started and completed the rectification process. In the case of the second failure, all participants immediately turned to the interface with determination.

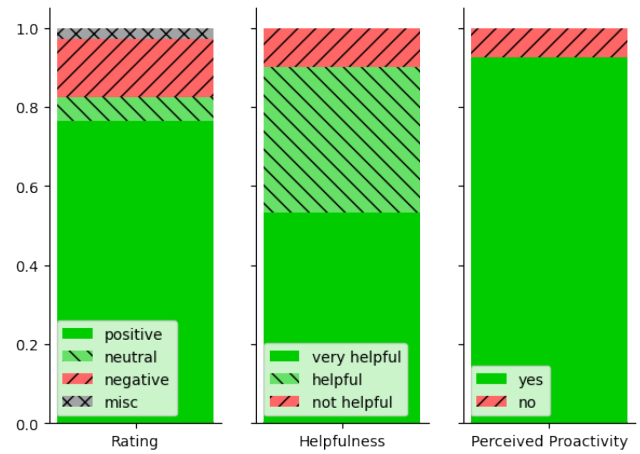

Figure 2: The left stacked bar depicts the responses to the rating (Q_1), and in the middle, the responses to the more specific question Q_2. The right bar reflects the responses to the perceived proactivity (Q_3) of the interface.

4 CONCLUSION AND FUTURE WORK

This paper introduces the FCFM and assesses its perception through a user study involving 35 participants. The findings suggest that the FCFM is a positive and helpful feature when dealing with cobot failures. Participants rated the graphical interface highly supportive for task processing, while the light modality did not yield similar positive outcomes, likely due to the cobot being obstructed from view by a perforated panel. These results emphasize the need for further empirical evaluations, specifically targeting different phases and modalities of the FCFM. The valuable feedback from participants should be included in future research, like the challenge of using gloves that complicate the use of a graphical interface. Notably, limitations exist, including unforeseen failures disrupting the experiment for 19 of the 35 participants. Those failures were due to various causes, such as an unintended opening of the gripper or a delay in the graphical interface, increasing waiting periods, or requiring a manual reset of the interface. While those unforeseen failures have to be dealt with properly in the future main analysis, the reported results focus on aspects, which ought to be not impacted by the unexpected failures. Moreover, the study was conducted in a laboratory setting, necessitating future field research. Currently, we are analyzing the impact of the FCFM's proactive and reactive configurations on user experience, trust, and frustration, and we will provide further results in the future. In summary, our preliminary investigation suggests that the FCFM offers intriguing benefits for cobot failures. However, implementing such frameworks requires consideration of potential social impacts. While granting workers more autonomy with failing cobots, it might also challenge existing job role hierarchies and knowledge distribution within production settings.

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