Human Nervous System-based Human-Robot Collaboration in Construction

Francis Baek and SangHyun Lee

Abstract—**Human-robot collaboration (HRC) is an emerging form of work anticipated to improve construction processes by combining human expertise with robotic automation. Considering responses of human workers (i.e., co-workers) can be crucial to enhance their performance and productivity in human-robot teams. However, studies primarily focused on advancing robotic capabilities without considering their potential impacts on co-workers. This research proposes a human nervous system-based HRC in construction, which aims for robots to leverage the nervous system's fundamental role in regulating human responses by: 1) understanding co-workers' nervous system activities across the brain and body; and 2) adapting their actions to promote desired responses. To this end, wearable biosensors, such as an EEG (electroencephalogram) headset and an EDA (electrodermal activity) wristband, have been utilized to analyze co-workers' responses. Additionally, a response-adaptive robot control strategy has been developed using a model-based reinforcement learning, which enables robots to consider each co-worker's nervous system activity to foster desired responses. Major results from simulated HRC with participants and real KUKA robots in lab environments showed that all participants' nervous system activities were significantly affected during HRC, which were also estimated to affect productivity in human-robot teams, presenting potential importance of considering co-workers' responses. Moreover, the proposed nervous system-adaptive robot control strategy demonstrated promising potential in promoting desired nervous system activities in co-workers during simulated HRC in virtual environments. The findings of this research are expected to serve as a solid foundation to provide insights into achieving more productive and cohesive human-robot teams in construction, grounded on co-workers' well-being.**

I. INTRODUCTION

Human-robot collaboration (HRC) has emerged as a new form of work in construction, which can combine the strengths of humans and robots [1]. Robots can take over physically demanding, dangerous, and repetitive tasks to make room for human workers to focus on dexterous, problem-solving, and decision-making tasks. The integration of robotic automation and human expertise through HRC has already shown promising potential to alleviate the industry's ongoing challenges, including stagnant productivity, high safety risks, and labor shortage [2].

While promising, HRC is still in its early stages of construction, requiring thorough analysis to realize its great potential. A potentially crucial aspect is collaborating with human workers' (co-workers') responses, encompassing physical, cognitive, and emotional. Previous studies have demonstrated that physical, cognitive, and emotional states, such as physical fatigue, cognitive load, and emotions like happiness, can be crucial to worker performance [3]. Additionally, studies in some fields, like social robotics, have identified that human responses can influence trust and acceptance of robots, which can affect cohesion between humans and robots [4]. The importance of co-workers' responses can be more pronounced within the co-robotic construction environments as a potentially crucial factor in realizing more productive and cohesive HRC.

A comprehensive understanding of how co-workers would physically, cognitively, and emotionally respond to robots can be essential to identifying the importance of the responses. However, the primary efforts of HRC in construction have only prioritized advancing robotic capabilities, such as speed, precision, and autonomy, with little attention paid to how the robots can affect co-workers' responses [5]. At the same time, promoting the desired responses in co-workers during HRC can become essential. A potential approach can involve robots recognizing and managing their impacts on co-workers' responses. However, robot control has primarily relied solely on performance-oriented factors, such as productivity and safety [5]. There remains a lack of effective methods for robots to consider both the performance-oriented factors and their co-workers' responses during HRC.

While co-workers' responses can become crucial factors in realizing the great potential of HRC in construction, there remain notable gaps in: 1) our understanding of co-workers' physical, cognitive, and emotional responses to robots; and 2) effective strategies for robots to consider the responses.

II. RESEARCH OBJECTIVES

To understand and promote desired responses in co-workers, this research proposes a human nervous system-based HRC consisting of two major phases: 1) understand human nervous system activity—an interconnected network throughout our body that fundamentally regulates human responses—during HRC to understand how humans will respond to robots; and 2) develop human nervous system-adaptive robot control strategy to promote desired human responses, which may lead to more productive HRC.

III. HUMAN NERVOUS SYSTEM AND RESPONSES

Human responses are fundamentally regulated by the nervous system [6]. By interpreting sensory inputs and coordinating appropriate changes across mind and body, the nervous system governs both involuntary (i.e., not willingly controllable) responses, such as increased heart rate, and voluntary (i.e., intentional) actions like conscious decision-making. These responses can manifest as short-term

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fluctuations, like surprise or tension, or accumulate into long-term effects, such as fatigue, anxiety, and depression. Physical, cognitive, and emotional responses are shaped by two major divisions of the nervous system (Figure 1): 1) the peripheral nervous system, which governs physical reactions, and 2) the central nervous system, comprising the brain and spinal cord, which underlies cognitive and emotional processes.

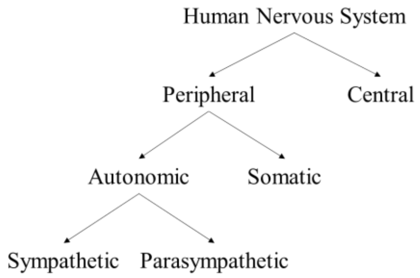

Figure 1. Human Nervous System.

Within the peripheral nervous system, the autonomic nervous system regulates involuntary physiological processes, such as heart rate, blood pressure, and respiration [7]. Its sympathetic nervous system is responsible for the body's fight-or-flight response, which refers to physiological activations like increased heart rate and skin conductance in response to stressful events [7]. The activation of the sympathetic nervous system (i.e., sympathetic arousal) can be influential to human performance by affecting muscle activation, movement speed, and strength [8].

Cognitive responses are primarily mediated by the central nervous system, which is related to mental functions, such as attention, perception, and memory [9]. Among these constructs, task engagement and vigilance can be critical to human performance, which can lead to different cognitive states, ranging from mind wandering to optimal for task conductance [9]. Task engagement reflects the demands on sensory processing during task conductance, and vigilance refers to alertness to external contingencies.

Emotional responses are also mediated by the central nervous system and can be represented by two constructs, valence and cortical arousal [10]. Valence refers to feelings from displeasure to pleasure, while cortical arousal reflects feelings from relaxation to excitement. Together, valence and cortical arousal are widely recognized as reliable and sufficient dimensions for representing emotional states, such as excitement, relaxation, boredom, and fear [10]. Changes in valence and arousal can influence how people appraise the causes of these changes. If a robot is perceived as the cause, their appraisal of robots can be changed, which can affect acceptance and trust toward robots [4].

IV. Research Phase #1

In phase #1, we examine co-workers' physical, cognitive, and emotional changes over short periods like seconds and minutes while collaborating with a robot. To this end, we recruited 40 participants to experience different collaborating conditions, such as the robot's different movement speeds, in a lab environment (Figure 2). The corresponding responses were analyzed by measuring the changes in the five constructs—sympathetic arousal, task engagement, vigilance, valence, and cortical arousal—using an EDA wristband sensor and an EEG headset.

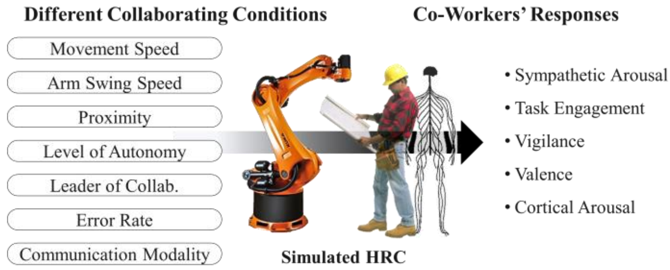

Figure 2. Overview of the method of Phase #1.

A. Bricklaying and Line-drawing Tasks with Participants

We recruited 40 students with diverse backgrounds, levels of construction experience, and familiarity with robots. Although these participants may not adequately represent a specific population, such as construction workers, their varied backgrounds were expected to exemplify different human responses during HRC, which are similarly anticipated from construction workers.

Among them, 20 participants completed a simulated bricklaying task with a KUKA KR 120 robot (Figure 3a). This demonstrates a significant task distribution between humans and robots, where robots assumed a physically demanding role, such as delivering bricks, while humans took on the dexterous role of laying the bricks in a line [11]. The bricklaying task was conducted in a lab at the University of Michigan. During the task, participants experienced varied conditions of the five parameters—robot's movement speed, arm swing speed, proximity, level of autonomy, and leader of collaboration—across different conditions, which were identified due to their potential different impacts on human responses from previous studies [12].

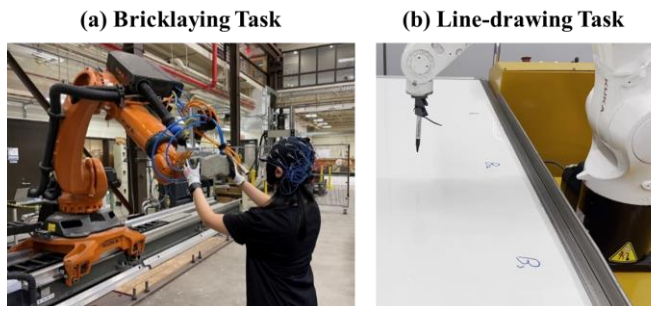

Figure 3. Bricklaying and line-drawing tasks.

The remaining 20 participants performed a simulated line-drawing task with a KUKA KR 60 robot (Figure 3b). This represents another major task distribution between humans and robots; robots conduct repetitive line-drawing when humans direct the path for the lines and supervise the quality [11]. The line-drawing task was conducted in a lab at Seoul National University in Korea. During the task, participants experienced varied conditions of the four parameters—task pace, error rate, leader of collaboration, and communication modality—across different conditions, which were identified due to their potential different impacts on human responses based on previous studies.

B. Response Monitoring using Wearable Sensors

During the bricklaying and line-drawing tasks, the EDA signal was analyzed to measure the levels of sympathetic arousal, reflecting physical responses. To this end, the EDA signal was processed using convex optimization to extract electrodermal response (EDR), reflecting the level of sympathetic arousal. Meanwhile, the EEG signal was analyzed to measure the levels of task engagement and vigilance for cognitive responses, and those of valence and cortical arousal for emotional responses. To this end, EEG signals were collected over the scalp, which are known to be responsive to cognitive and emotional responses. Noise reduction techniques, such as wavelet independent component analysis, were applied to alleviate artifacts. Then, EEG signals were analyzed across different frequency ranges that are known to be correlated with the four constructs of the cognitive and emotional responses.

C. Analysis, Results, and Discussion

Multiple linear regression was applied (1), which allows us to examine the relationships between independent and dependent variables in an easily interpretable and statistically reliable model . We considered the five constructs of physical, cognitive, and emotional responses as dependent variables and the parameters of HRC as independent variables.

$$Y = f(X) + g(X, time) \tag{1}$$

where X is the parameters of HRC and Y is human responses

F-tests of overall significance reveal that all participants' responses were significantly affected during HRC. Additionally, t-tests on the regression coefficients reveal that all participants' responses significantly varied over time. Moreover, the nested regression analysis reveals that responses of almost every pair of participants (97%) were different.

Meanwhile, we also estimated the productivity in human-robot teams in terms of the parameters of HRC. As the estimations of co-workers' responses using regression models and the team productivity have an identical basis, this allowed us to explore the concurrent changes in co-workers' responses and team productivity given the conditions of the parameters. Based on this setup, we tried to answer the two questions: 1) if HRC prioritizes productivity, how does it affect co-workers' responses?; and 2) if HRC prioritizes co-workers' responses, how does it affect team productivity? To answer these questions, we quantitatively defined optimal physical, cognitive, and emotional responses that can lead to optimal human performance. Based on previous studies, humans are known to optimally perform when they exhibit: 1) moderate sympathetic arousal; 2) moderate task engagement; 3) moderate vigilance; 4) positive valence; and 5) positive cortical arousal [9,10,13].

Results demonstrated that although human-robot teams could achieve high productivity when HRC prioritized productivity, none of the co-workers were estimated to exhibit the optimal responses (TABLE 1). In contrast, when HRC prioritized co-workers' responses, all co-workers were expected to exhibit the optimal responses. However, considering responses could cause a significant loss in productivity. As a workspace, HRC may prioritize productivity. However, when co-workers struggle, if robots can adapt to co-workers' responses and foster desired responses, it can be an effective way to balance productivity and co-workers' responses. These results present the potential of robot adaptation to co-workers' responses as a way to balance co-workers' responses and team productivity.

TABLE 1. Productivity and co-workers' responses.

Priorities	Tasks	# of Optimal Responses	Estimated Team Productivity
Productivity	Brick	0	314 bricks/team-hr
	Line	0	2.71 m/team-min
Responses	Brick	20	240 bricks/team-hr
	Line	20	2.31m/team-hr

V. RESEARCH PHASE #2

Given the potential of robot adaptation to co-workers' responses, this research develops a response-adaptive robot control strategy, which aims for robots to consider and foster desired responses in co-workers. We applied a model-based reinforcement learning (RL) [14], a classical branch of machine learning for adaptive robot control.

A. Model-based Reinforcement Learning

While RL holds great potential for adaptive robot control, applying RL to adapt to human responses is not straightforward. The complicated nature of human responses, such as changing over time and varying among individuals, can challenge RL training by causing 1) Markov assumption violation, 2) non-stationary environment, and 3) hard-to-generalize policy. To overcome such challenges, this research integrates our prior findings with a model-based RL. In our prior study, we demonstrated that multiple linear regression modeling could reliably represent each co-worker's responses. Providing these models enables robots to learn regression coefficients tailored to each co-worker, instead of exploring their responses from scratch, which can facilitate stable and reliable adaptation.

The proposed robot control strategy lets a robot operate iteratively by 1) taking an action, 2) learning the co-worker's physical, cognitive, and emotional responses, and 3) planning the next action to promote the desired co-worker's responses (Figure 4). Notably, the robot is assumed to monitor co-workers' responses through wearable sensors, such as a wristband EDA sensor for physical response and an EEG headset for cognitive and emotional responses.

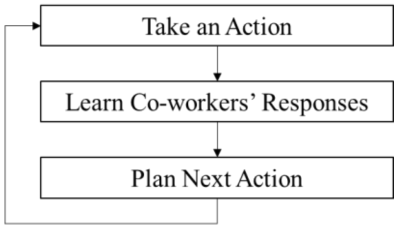

Figure 4. Overview of the proposed robot control strategy.

B. Bricklaying and Line-drawing in Virtual Environments

As an early attempt to validate the effectiveness of the proposed robot control strategy in adapting to co-workers' responses, we simulated HRC with virtually simulated co-workers' responses in virtual environments for bricklaying and line-drawing tasks. We created virtual environments that replicate the lab environments, where the bricklaying and line-drawing tasks were conducted in Phase #1. In the virtual environments, a virtual robot collaborated with 40 virtual co-workers, 20 for the bricklaying task and 20 for the line-drawing task. The responses of virtual co-workers were simulated by using their regression models obtained from Phase #1, which allowed for the estimation of physical, cognitive, and emotional responses to the robot's actions. By interacting with these virtual co-workers, the robot could learn their responses over interactions through the proposed response-adaptive robot control strategy.

C. Results and Discussion

In order to quantitatively evaluate the effectiveness of the proposed robot control strategy in considering co-workers' responses, we defined a metric, response score (2), which is the number of constructs that are at optimal states out of five. If the response score is 5, it means that co-workers' physical, cognitive, and emotional responses are optimal.

$$\text{Response Score (0 to 5)} = \text{\# of Optimal Constructs} \quad (2)$$

The proposed strategy effectively improved co-workers' responses, achieving a response score greater than 4 out of 5 for both bricklaying and line-drawing tasks (TABLE 2). Notably, when the robot prioritized productivity, the response score was only around 2. Our results present the proposed personalized response-adaptive robot control strategy as an effective strategy to promote desired co-workers' responses.

TABLE 2. Comparison of robot control strategies.

Strategies	**Tasks**	**Response Score**	**Estimated Team Productivity**
Productivity Prioritized	Brick	2.12	314 bricks/team-hr
	Line	2.44	2.71 m/team-min
Response Adaptive	Brick	4.32	236 bricks/team-hr
	Line	4.27	2.34 m/team-hr

This study proposes a response-adaptive robot control strategy using a model-based RL, which enables robots to learn each co-worker's physical, cognitive, and emotional responses to foster their desired status during HRC. While co-workers' responses can vary during HRC, the simulated HRC in virtual environments for bricklaying and line-drawing tasks demonstrated the potential effectiveness of the proposed robot control strategy in fostering desired responses in co-workers from the two major forms of HRC.

The proposed model-based RL approach allows reliable and scalable adaptation to co-workers' responses, even when interacting for the first time. Additionally, by modeling and storing each co-worker's responses, the approach can facilitate future interactions, having already learned their responses. As the robot does not need to start from scratch, subsequent collaborations can become more quickly adaptive to each co-worker's responses.

VI. Conclusion

While the primary focus of HRC has been on advancing robotic capabilities, this research demonstrated the importance of co-workers' physical, cognitive, and emotional responses as potentially crucial aspects that can influence co-workers' performance, productivity, and cohesion in human-robot teams. To consider responses, this research also proposes a response-adaptive robot control strategy, which is expected to contribute to fostering desired responses in co-workers. Findings of this research are expected to lay a solid foundation to provide insights into more productive and cohesive human-robot teams in construction, grounded on co-workers' physical, cognitive, and emotional well-being.

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