Personalized Emotion-Adaptive Robot Control Strategy for Human-Robot Collaboration in Construction

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Abstract

While human-robot collaboration (HRC) is anticipated to improve construction productivity and safety, it can become crucial to manage emotional responses of collaborating human workers (co-workers) during HRC due to their critical impacts on co-workers' performance and human-robot cohesion. A potential approach involves controlling robots in ways that can adapt to potentially different emotional responses of co-workers to foster desired responses and productivity in human-robot teams. However, we still lack an effective method as existing robot control strategies tend to prioritize productivity and safety alone or consider co-workers' responses but take standardized actions across different co-workers. In this study, we propose a personalized emotion-adaptive robot control strategy using model-based reinforcement learning (RL), which aims for robots to learn each co-worker's emotional responses over interaction to plan and take actions for fostering desired responses while pursuing high productivity in human-robot teams. The effectiveness of the proposed robot control strategy was demonstrated in a virtual environment by simulating HRC with the emotional responses of 20 co-workers for a construction task. Results showed that a robot with the proposed strategy could promote desired emotional responses like happiness in all 20 co-workers for approximately 37 minutes during a 1-hour bricklaying task. While findings demonstrate the potential of the proposed robot control strategy as a way for robots to adapt to co-workers' emotional responses, further analysis will be anticipated to minimize potential trade-offs in productivity in human-robot teams that may arise from considering co-workers' responses.

Keywords –

Human-Robot Collaboration, Reinforcement Learning, Emotional Response

1 Introduction

The construction industry has suffered from stagnant productivity growth compared to other industries [1]. According to the McKinsey Global Institute, the productivity (real gross value added per labor hour) of the construction industry has grown 1% for the past two decades since 1995, while the average annual growth by the total global economy was 2.8% [2]. Although construction productivity can be considered mainly relying on labor power [3], labor power can be negatively affected by other ongoing issues in the industry, including high safety risks, the aging workforce, and the labor shortage [4-6]. The stagnant growth of productivity has remained a major challenge.

Human-robot collaboration (HRC) has recently gained attention in the construction industry, envisioned as a new paradigm shift toward co-robotic construction [7]. Recent advancements in robotic technology have introduced collaborative robots, an evolved form of conventional industrial robots, enabling collaboration with humans by combining the strengths of humans and robots [8]. For example, robots can take over physically demanding, dangerous, and repetitive tasks for human workers to focus on dexterous, problem-solving, and decision-making tasks [8]. HRC is anticipated to improve construction productivity by reducing the primary dependence on workers' labor power and increasing the level of robotic automation [9].

However, HRC is in its early stages in construction. The extent of its impact on construction productivity has not been thoroughly examined [9]. A potentially crucial factor for productive HRC is emotional response of collaborating human workers (co-workers). Emotions can be defined as mental states, associated with degrees from displeasure to pleasure and from relaxation to excitement, such as excitement, relaxation, boredom, and fear [10]. Studies have demonstrated that emotions can cause critical impacts on worker performance by affecting decision-making, problem-solving, and behaviors [11]. Additionally, studies in some fields, like social robotics, have identified that emotions can be largely influential to the human-robot cohesion by influencing acceptance and trust toward robots [12]. Within the unprecedented co-robotic work environment, the importance of emotions can become more considerable than before to achieve the anticipated productivity growth by the human-robot teams.

Efforts have identified the potential variations in co-workers' emotional responses during HRC. Our prior work demonstrated through a lab experiment that the emotional responses of co-workers could be significantly influenced during a simulated bricklaying task with a real robot [13]. Major results showed that while every co-worker's emotional response was affected, almost every co-worker exhibited statistically different responses, which were also estimated to affect productivity in human-robot teams. These findings present that considering co-workers' emotional responses, which may vary among individuals, can become essential for fostering desired responses that can enhance both their performance as well as cohesion with robots.

A potential approach can involve controlling robots in a way that can consider each co-worker's emotional responses. However, the consideration of emotional responses has not been a major focus in robot control strategies for HRC, particularly in construction, where performance-oriented factors like productivity and safety remain the primary objectives [14,15]. While a few studies have presented the potential necessity of robot control that considers human responses [16], robots typically take standardized actions for all individuals, which may be ineffective for co-workers with different responses [13]. As such, we still lack an effective robot control strategy for robots to consider co-workers' potentially different emotional responses while pursuing higher productivity in human-robot teams.

In this study, we propose a personalized emotion-adaptive robot control strategy that aims for robots to learn each co-worker's emotional response during interactions, even with whom they encounter for the first time. This strategy allows robots to take actions that can elicit desired emotional responses (e.g., happiness and excitement), which can enhance co-workers' performance and cohesion with robots, while pursuing high productivity in human-robot teams. The proposed robot control strategy is based on reinforcement learning (RL) algorithm, an effective branch of machine learning for adaptive robot control [17]. The effectiveness of the proposed robot control strategy was evaluated through a simulated HRC for a construction task in a virtual environment, where the robot collaborated with virtually simulated 20 co-workers, whose emotional responses were identified in our prior study [13].

This study demonstrates the potential effectiveness of using reinforcement learning (RL) for an adaptive robot control strategy to promote desired emotional responses in each co-worker, including those encountered for the first time. At the same time, the findings present the need for further analysis of robot control to balance emotional responses and productivity in human-robot teams, as trade-offs between these factors may arise.

2 Model-based Reinforcement Learning for Personalized Emotion-Adaptive Robot Control Strategy

The proposed robot control strategy relies on a model-based RL, an effective branch of RL when interacting with complicated environments like human responses [18]. Model-based RL allows the robot to learn the mechanisms of co-workers' emotional responses to its actions through modeling over interactions. This enables the robot to plan and take actions for fostering desired emotional responses in co-workers while pursuing high productivity in human-robot teams. The proposed robot control strategy guides the robot to operate iteratively by 1) taking an action during HRC for a construction task (Figure 1a), 2) learning the co-worker's emotional responses (Figure 1b), and 3) planning the next action to promote desired co-worker's emotional responses and highest possible productivity in human-robot teams (Figure 1c). Notably, it is assumed that the robot can monitor co-workers' emotional responses through wearable sensors, such as brainwave analysis using an EEG headset.

2.1 Desired Emotional Response

Emotional response can be represented using a bipolar dimensional emotion model [19], which reliably and sufficiently captures emotional states (e.g., excited and bored) by estimating emotional status based on two key dimensions (Eq. 1): valence (ranging from displeasure to pleasure) and arousal (ranging from relaxation to excitement). Among various emotional

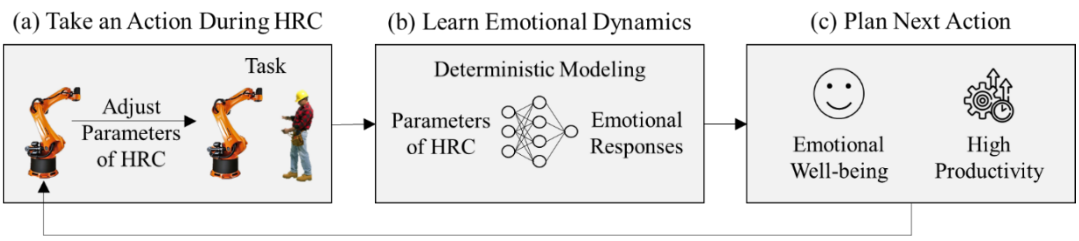

Figure 1. Overview of the proposed robot control strategy.

states, including calmness, anxiety, and boredom, this study considered positive emotions, such as happiness and excitement, as desired. The positive emotions are represented by positive valence and arousal, known to promote cohesive human-robot relationships and help co-workers with better performance while staying alert to potential safety risks in ever-changing, unstructured, and hazardous construction work environments [11,12,20].

$$e = \{valence, arousal\} \qquad \text{(Eq. 1)}$$

2.2 Take an Action

In RL, the actions of a robot refer to changes in the state of the environment, which encompasses everything that the robot observes and responds to [17]. In this study, the environment is represented by the states (s_t), consisting of 1) parameters of HRC (p_t), such as robot's movement speed, which can affect co-workers' emotional responses, and 2) the corresponding emotional responses of a co-worker (e_t) at a time t (Eq. 2.1). Actions (a_t) of a robot refer to the adjustments in parameters of HRC (p_{t+1}) during a construction task, such as an updated movement speed after slowing down (Eq. 2.2). The actions directly adjust the parameters of HRC and can cause variations in emotional responses of a co-worker. Over the interaction, the robot can collect the set (D) of observations, consisting of current states (s_t), robot's action (a_t), and corresponding changes in environmental states (s_{t+1}) (Eq. 2.3). It is noteworthy that the size of D expands whenever the robot takes an action.

$$s_t = \{p_t, e_t\} \qquad \text{(Eq. 2.1)}$$

$$a_t = p_{t+1} \qquad \text{(Eq. 2.2)}$$

$$D = \{(s_t, a_t, s_{t+1})_{t=1 \sim T}\} \qquad \text{(Eq. 2.3)}$$

$$\begin{gathered} where\ s_t\ and\ a_t\ represent\ the\ state\ and\ action, \\ respectively, at\ each\ time\ step\ t, \\ ranging\ from\ the\ beginning\ (t=1) \\ to\ the\ current\ time\ step\ (t=T) \end{gathered}$$

2.3 Learn Co-worker's Emotional Responses

In this study, the proposed strategy is specifically tailored to operate within a deterministic Markov decision process framework, where the environment's transitions are deterministic given the current state and action. The set of observations, D, enables the robot to learn the deterministic state transition model $T(s_{t+1}|s_t, a_t)$ (Eq. 3), which predicts how the state (s_t) evolves based on the robot's action (a_t). As actions (a_t) correspond to the updated parameters of HRC (p_{t+1}), the learning of the transition model solely focuses on $f_{Emotion}$, which represents co-workers' emotional responses to the robot's actions. The structure of $f_{Emotion}$ can be flexibly specified when previously identified relationships exist between the robot's actions and co-workers' emotional responses. For example, in our prior study, we identified multiple linear regression relationships between robot actions, such as movement speed, and co-workers' emotional responses [13]. During interactions, the robot learns coefficients of $f_{Emotion}$ tailored to the specific co-worker using the least square optimization (Eq. 3).

$$\begin{gathered} T(s_{t+1}|s_t, a_t) = \{a_t, f_{Emotion}(a_t)\} \qquad \text{(Eq. 3)} \\ where\ s_{t+1} = T(s_t, a_t) = \{p_{t+1}, e_{t+1}\}, \\ p_{t+1} = a_t, and \\ f_{Emotion}(a_t)\ minimizes\ \sum_t \|e_{t+1} - f_{Emotion}(a_t)\|^2 \end{gathered}$$

2.4 Plan the Next Action

While the robot's actions can affect co-worker's emotional responses, they also can affect the productivity of human-robot teams. For example, the robot's faster movement speed can enhance productivity in human-robot teams. We assume the robot can estimate the productivity of human-robot teams in terms of the parameters of HRC ($f_{Productivity}$) (Eq. 4). Based on the estimations, $f_{Emotion}$ and $f_{Productivity}$, the robot uses its policy to select the next action a_t^*, aiming to maximize the cumulative reward $r(s_t, a_t)$ (Eq. 4), which can lead to the highest possible productivity in human-robot teams among the candidate actions that can evoke co-workers' emotional well-being. Notably, while traditional RL framework often uses value functions to represent expected cumulative rewards, this study focuses on direct optimization of immediate rewards $r(s_t, a_t)$ using the transition model $f_{Emotion}$. Using a value function to predict cumulative rewards over longer term can be challenging in the context of human response-adaptive robot control, as human responses may change over time even in short periods (e.g., seconds). In this context, we propose the robot focus on immediate rewards, which can allow effective respond to emotional responses. However, for this planning approach to be effective, the robot must first observe co-workers' emotional responses across a wide range of scenarios to accurately learn the transition model. To achieve this, the robot incorporates an exploration strategy, randomly selecting a percentage of its actions to gather diverse data on co-workers' responses. Initially, 100% of the robot's actions are random until collecting 48 observations of co-worker's emotional responses, and this percentage decreased to 20%. This empirically determined strategy balances exploration and exploitation, enabling the robot to refine its transition model and improve action planning over the interaction.

$$a_t^* = \underset{a}{\text{argmax}} \sum_a r(s_t, a_t) \qquad \text{(Eq. 4)}$$

$$where\ r(s_t, a_t) = \begin{cases} f_{Productivity}(p_{t+1} = a_t) & if\ f_{Emotion}(a_t) > 0 \\ 0 & Otherwise \end{cases}$$

3 Simulated HRC for a Construction Task in a Virtual Environment

In our prior study, we analyzed the emotional responses of 20 people, consisting of 13 men and 7 women, while they collaborated with a real robot in a lab environment for a bricklaying task, which can be considered a representative example of distributing tasks between humans and robots in construction [13]; robots take over physically demanding tasks (e.g., lifting bricks) while workers focus on the dexterous tasks like finishing. Participants were recruited from students with various academic backgrounds (mean age: 29; standard deviation of age: 3.5; minimum age: 23; and maximum age: 36), including 12 from civil and environmental engineering, some with construction field experience, 4 from other engineering departments like electrical and mechanical, and 4 from non-engineering departments like music and social science. Their varying levels of construction experience, technical proficiency, and exposure to robotic technologies were expected to exemplify a wide range of emotional responses during HRC, also anticipated among construction workers. As an early attempt to demonstrate the potential effectiveness of the proposed robot control strategy in adapting to wide spectrum of different emotional responses, we adopted the emotional responses of the student participants, instead of exploring and simulating emotional responses of construction workers, whose responses might be affected by occupational biases, such as concerns of job loss and replacement by robots [21].

In this context, we virtually simulated a robot to collaborate with each of the 20 co-workers to conduct a bricklaying task for one hour, a plausible work duration before a break. We replicated the lab environment from the prior study [13] within a virtual environment, where parameters of HRC and emotional responses were computationally simulated. The bricklaying task was conducted by a team of one co-worker and one robot (Figure 2); the robot delivered bricks for the co-worker to lay them in a line. Notably, the simulated bricklaying task conducts some portion of masonry work to demonstrate the effectiveness of the proposed robot control strategy during a representative task distribution between humans and robots, rather than replicating the entire masonry process, including scaffold installation, mortar mixing, and brick cutting.

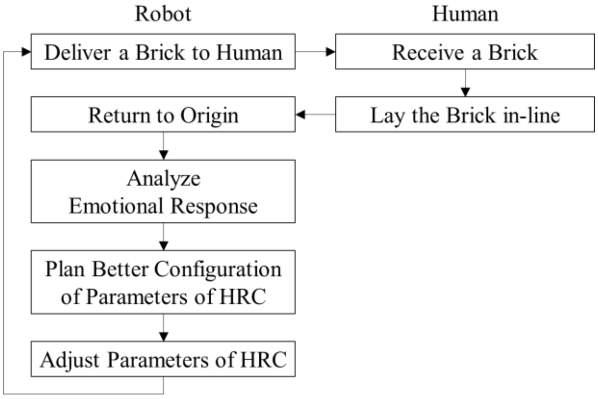

Figure 2. Workflow of the bricklaying task.

The robot was allowed to take actions over five parameters of HRC, which were identified to affect co-workers' emotional responses [13]: 1) robot's movement speed; 2) robot's arm swing speed; 3) proximity between humans and robots; 4) level of autonomy; and 5) leader of collaboration. All the actions were to be made within the specified ranges based on the robot's capability and physical dimension of the lab environment [13]: movement speed from 27.8 cm/s to 143.8 cm/s; arm swing speed from 23.8 cm/s to 109.1 cm/s; proximity as either direct (100 cm) or indirect (200 cm); level of autonomy as either manual or auto; and leader as either human or robot.

In response to the robot's actions, the emotional responses of 20 co-workers were virtually simulated by using two regression models, one for valence and another for arousal, which were obtained from the prior study (Eq. 5.1) [13]. Given robot's actions, these regression models estimate the corresponding valence and arousal of a co-worker at a given time (sec) since the start of HRC. While the robot is aware of these regression models as the $f_{Emotion}$ (Eq. 3), it does not know the coefficients specific to any co-worker but should learn the coefficients tailored to each co-worker through interactions. It is assumed that the robot observes a co-worker's valence and arousal by analyzing EEG signals collected via EEG headset.

Notably, the regression models (Eq. 5.1) were obtained by analyzing EEG signals with noise reduction techniques, including wavelet independent component analysis, which have been demonstrated to be effective in alleviating artifacts—such as eye-blinks, heart rate, and muscle movement—common sources of noise in EEG signals, even in onsite construction settings. However, despite noise reduction, EEG signals can still be affected by noise. In this regard, the estimates for each co-worker were adjusted using means, standard deviations, and noise parameters derived from EEG-based valence and arousal measurements in the prior study (Eq. 5.2) [13].

$$y_i = c_1x_1^2 + c_2x_1 + c_3x_2^2 + c_4x_2 + c_5x_3 + c_6x_4 + c_7x_5 + c_8(Time) + \beta \quad \text{(Eq. 5.1)}$$

$$where\ y_i = \begin{cases} Valence \\ Arousal \end{cases},$$

$$x_j = \begin{cases} Move\ Speed \\ Arm\ Speed \\ Proximity \\ Level\ of\ Autonomy \\ Leader\ of\ Collaboration \end{cases}, \beta = constant,$$

$$and\ Time\ is\ the\ elapsed\ time\ of\ HRC\ (sec)\ since\ the\ start\ of\ HRC$$

$$\tilde{y}_i = \sigma_i y_i + \mu_i + \epsilon_i \quad \text{(Eq. 5.2)}$$

$$where\ \epsilon_i \sim N(0, \delta_i^2), and\ \sigma_i, \mu_i, and\ \epsilon_i\ denote\ standard\ deviation, mean, and\ noise\ of\ y_i$$

The robot could estimate productivity in human-robot teams according to its actions during the bricklaying task (i.e., $f_{Productivity}$ in Eq. 4) by following the method used in the prior study [13]. The estimated productivity was represented by the number of bricks laid for one hour by a human-robot team in terms of the five parameters of HRC. Specifically, the bricklaying times for one robot and one human based on five HRC parameters were calculated (Eq. 6.1 and 6.2) and then aggregated into a human-robot team's bricklaying time (Eq. 6.3), which was subsequently converted into the number of bricks for one human-robot team-hour (Eq. 6.4).

$$\begin{aligned} &Time\ (sec) for\ a\ robot\ to\ lay\ a\ brick \\ &= Body\ Traverse\ Time + Arm\ Traverse\ Time + Delay\ by\ Manual\ Control \\ &= \frac{Body\ Travel\ Distance}{Movement\ Speed} + \frac{Arm\ Travel\ Distance}{Arm\ Swing\ Speed} + 1(Manual) * \alpha \quad \text{(Eq. 6.1)} \end{aligned}$$

$$where\ Body\ Travel\ Distance\ is\ 6.1m,\ Arm\ Travel\ Distance\ is\ 2.4m,\ and\ \alpha\ is\ delay\ of\ 3\ seconds\ by\ the\ manual\ control$$

$$\begin{aligned} &Time\ (sec)\ for\ a\ human\ to\ lay\ a\ brick \\ &= Bricklaying\ \ Time + Delays\ by\ Indirect\ Proximity\ and\ Human\ Leader \\ &= \ Bricklaying\ \ Time + 1(Human\ Leader) * \beta + 1(Indirect) * \gamma \quad \text{(Eq. 6.2)} \end{aligned}$$

$$where\ Bricklaying\ Time\ is\ 5\ seconds,\ \beta\ is\ delay\ of\ 1\ sec\ by\ human\ leader,\ and\ \gamma\ is\ delay\ of\ 2\ sec\ by\ the\ indirect\ proximity$$

$$\begin{aligned} &Time\ (sec)\ for\ a\ Human\text{–}Robot\ team\ to\ lay\ a\ brick \\ &= (Eq. 5.1) + (Eq. 5.2) \quad \text{(Eq. 6.3)} \end{aligned}$$

$$\begin{aligned} &Estimated\ Team\ Productivity \\ &= \left\{\frac{1\ Brick}{(Eq. 6.3)\ Team\text{–}sec}\right\} \times \left(\frac{3{,}600\ Team\text{–}sec}{Team\text{–}hour}\right) \\ &= \frac{3{,}600}{Eq. 5.3}\ Bricks\ per\ Team\text{–}hour \quad \text{(Eq. 6.4)} \end{aligned}$$

We compared four types of robot control strategies (Table 1). The first type only prioritized productivity without considering co-workers' emotional responses, representing the currently predominant approach of robot control during HRC. For example, the robot would maximize its movement speed for high productivity. The second type employed a standardized planning approach, which takes uniform actions across different co-workers. Specifically, the robot first identified a set of actions that were effective in evoking positive emotional responses (e.g., positive valence and arousal) and high productivity for a specific co-worker. This co-worker was selected because the emotional responses were the most similar to those of as many other co-workers as possible. The identified actions were then applied uniformly to all other co-workers. The third type is the proposed personalized emotion-adaptive robot control strategy, which would allow the robot to learn the emotional responses of each co-worker, leading it to take actions for fostering positive emotional responses while pursuing high productivity.

Table 1. Four Types of Robot Control Strategies.

Four Types		Consistency	Objectives
1	Productivity-prioritized (Represent Practice)	Same for All People	• Maximum Productivity
2	Standardized Emotion-Adaptive (Represent Other Studies)	Same for All People	• Maximum Productivity • Positive Emotions
3	Personalized Emotion-Adaptive (Proposed Behavior)	Personalized	
4	Fully Emotion-Aware (Ground Truth)	Personalized	

The fourth type represents the theoretical optimum (ground truth) when a robot is fully aware of the emotional responses of co-workers (i.e., regression models of Eq. 4) even before encountering them. This type of robot control may not be practical but can provide insights into how the robot can behave if it is fully aware of co-worker's emotional responses as an ideal case.

We specifically compared the four types of robot control strategies in terms of 1) the number of virtual co-workers who exhibited the desired emotional responses during the 1 team-hour of bricklaying, 2) the average duration of the desired emotional responses across the 20 co-workers, and 3) the average of the number of bricks laid for 1 team-hour. Notably, the robot with the proposed control strategy spent 15 minutes with each co-worker prior to the bricklaying task, as this time was required to initially explore and understand the co-workers' emotional responses.

4 Results and Discussion

The proposed personalized emotion-adaptive robot control strategy could promote the desired positive emotional responses for all 20 virtual co-workers (100%) for around 37 minutes during the 1 hour of simulated bricklaying task (3rd type in Table 2). Every co-worker could experience positive emotions for at least 20 minutes. The results present the potential effectiveness of the proposed robot control strategy in promoting desired emotional responses in co-workers, which can be critical to enhance co-workers' performance and human-robot cohesion for better productivity in human-robot teams.

The comparison of these results with those of the first and second types of robot control strategies is particularly noteworthy. These strategies could only promote positive emotional responses in 5 and 7 virtual co-workers, respectively, and the average durations of positive emotions across 20 co-workers were 15 minutes and 21 minutes, respectively. Although the strategies were effective for some virtual co-workers to exhibit positive emotions during the entire 60 minutes of bricklaying, they were not effective at all for the majority of virtual co-workers. These results present that promoting desired emotional responses in co-workers can require deliberate efforts to consider each co-worker's potentially different emotional responses. Otherwise, prolonged HRC with negative emotional status (e.g., anxiousness and fear) can cause co-workers to have reduced trust in robots, decreased collaboration efficiency, and potentially lead to psychological discomfort or stress, ultimately affecting the overall productivity and cohesiveness of human-robot teams [11,22].

It is noteworthy that the proposed robot control strategy enables the robot to execute personally different actions by considering individuals' emotional responses. As shown in Figure 3, the robot's actions were quite different to different co-workers. While emotional responses can be different among individuals, the proposed robot control strategy holds potential to consider each co-worker's emotional responses for fostering desired responses during HRC.

While promising, however, the proposed robot control strategy still has a room for improvement. The fourth type of robot control strategy shows that all 20 virtual co-workers could theoretically exhibit the positive emotions for around 58 minutes during the bricklaying task, while laying a greater number of bricks. These results present that advancing the proposed robot control strategy to promote desired emotional responses in co-workers for longer duration while maintaining higher productivity can be a direction for improvement.

Meanwhile, although the first type of robot control strategy was not effective in promoting positive emotions in co-workers, it could achieve higher productivity in human-robot teams compared to the proposed and the ideal robot control strategies (types 3 and 4 in Table 2). This can be interpreted that considering and promoting co-workers' desired responses may sacrifice the productivity in human-robot teams.

Such a potential loss in productivity in human-robot

Table 2. Emotional Responses and Productivity by the Four Types of Robot Control Strategies.

Four Types	# of Co-workers w/ Positive Emotions	Avg. Duration of Positive Emotions	Est. Productivity in Human-Robot Teams
1	5 out of 20 (25%)	15 mins (Min: 0, Max: 60)	314 bricks per one team-hour
2	7 out of 20 (35%)	21 mins (Min: 0, Max: 60)	256 bricks per one team-hour
3	20 out of 20 (100%)	37 mins (Min: 20, Max: 60)	244 bricks per one team-hour
4	20 out of 20 (100%)	58 mins (Min: 20, Max: 60)	286 bricks per one team-hour

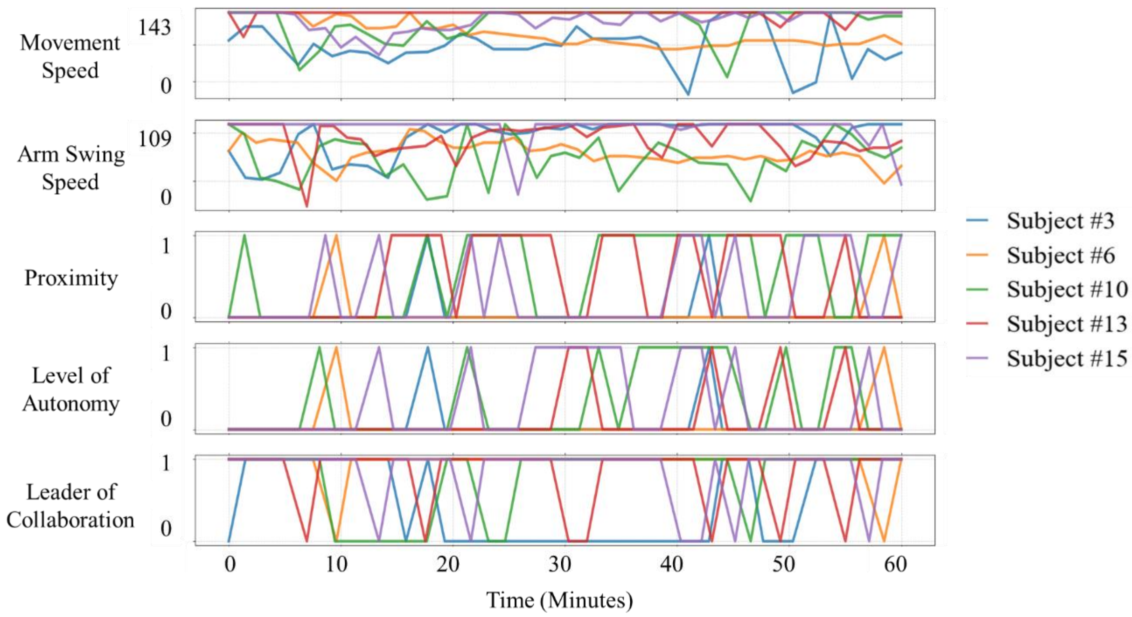

Figure 3. Robot's actions to five different subjects during the bricklaying task.

teams while promoting desired emotional responses in co-workers can raise ethical questions. For example, to what extent is a productivity loss acceptable to ensure co-workers' emotional well-being? Conversely, to what extent can a sacrifice in co-workers' emotional responses be justified to enhance productivity? This presents the clear need for further analysis regarding how we can balance emotional well-being and productivity, particularly in the construction industry, where productivity is crucial.

Grounded on the findings of this study, our future study can be two-fold: 1) demonstrate the effectiveness of the personalized adaptive robot control strategy during the interaction with actual co-workers, as this study simulated the responses of co-workers using the regression models; and 2) examine its effectiveness in other types of HRC in construction, which can involve HRC for different construction tasks, HRC with different construction robots, and HRC without direct physical interactions between humans and robots. The findings of this study are expected to provide a solid foundation for future research, aiming to achieve the emotional well-being of co-workers as well as more productive HRC in construction.

5 Conclusion

Emotions are crucial human responses, affecting human performance and human-robot cohesion, which can be potentially important for the success of HRC in construction. In this study, we propose a robot control strategy that aims to promote desired emotional responses in each co-worker while pursuing the high productivity of human-robot teams. We demonstrated the effectiveness of the proposed robot control strategy by comparing it with predominant strategies of robot control, such as those prioritizing productivity or standardized across people, through a simulated bricklaying task in a virtual environment with 20 people as co-workers. The proposed robot control strategy could lead to the desired positive emotions in all 20 co-workers for around 37 minutes during the 1-hour bricklaying task. Our results present the proposed personalized emotion-adaptive robot control strategy as an effective strategy to aim for promoting desired co-workers' emotional responses, which can contribute to enhancing co-workers' performance and human-robot cohesion. At the same time, the results raise a major question about how we can minimize the potential sacrifice in productivity in human-robot teams, which may arise as we consider co-workers' responses. While future research are expected, aiming to demonstrate the effectiveness of the proposed robot control strategy with actual co-workers for different construction tasks, the findings of this study can serve as a solid foundation to achieve more productive and cohesive human-robot teams in construction.

References

[1] L. Sveikauskas, S. Rowe, J.D. Mildenberger, Measuring productivity growth in construction, Monthly Lab. Rev. 141 (2018) 1.

[2] McKinsey Global Institute, Reinventing Construction: A Route To Higher Productivity,

Washington, D. C., 2017. http://www.mckinsey.com/industries/capital-projects-and-infrastructure/our-insights/reinventing-construction-through-a-productivity-revolution (accessed February 17, 2022).

[3] A.M. Jarkas, C.G. Bitar, Factors affecting construction labor productivity in Kuwait, Journal of Construction Engineering and Management 138 (7) (2012) 811-820.

[4] R. Sacks, A. Perlman, R. Barak, Construction safety training using immersive virtual reality, Construction Management and Economics 31 (9) (2013) 1005-1017.

[5] N.V. Schwatka, L.M. Butler, J.R. Rosecrance, An aging workforce and injury in the construction industry, Epidemiologic reviews 34 (1) (2012) 156-167.

[6] Skilled Labor Shortage: Persistent Challenge, Modern Contractor Solutions. https://mcsmag.com/skilled-labor-shortage-persistent-challenge/ (accessed February 3, 2022).

[7] C.-J. Liang, X. Wang, V.R. Kamat, C.C. Menassa, Human–robot collaboration in construction: Classification and research trends, Journal of Construction Engineering and Management 147 (10) (2021) 03121006.

[8] A. Vysocky, P. Novak, Human-Robot collaboration in industry, MM Science Journal 9 (2) (2016) 903-906.

[9] M. Wu, J.-R. Lin, X.-H. Zhang, How human-robot collaboration impacts construction productivity: An agent-based multi-fidelity modeling approach, Advanced Engineering Informatics 52 (2022) 101589.

[10] E.A. Kensinger, Remembering emotional experiences: The contribution of valence and arousal, Reviews in the Neurosciences 15 (4) (2004) 241-252.

[11] G.A. Fordjour, A.P. Chan, P. Amoah, A.A. Fordjour, Exploring the effects of occupational psychological disorders on construction employees and the construction industry, Occupational diseases and environmental medicine 8 (01) (2020) 1.

[12] S.H.-W. Chuah, J. Yu, The future of service: The power of emotion in human-robot interaction, Journal of Retailing and Consumer Services 61 (2021) 102551.

[13] F. Baek, D. Kim, G. Lee, B. Choi, S. Lee, Emotional Response Modeling for Human-Robot Collaboration in Construction., The 22nd International Conference on Construction Applications of Virtual Reality, Seoul, Korea, 2022.

[14] R. Li, Z. Zou, Enhancing construction robot learning for collaborative and long-horizon tasks using generative adversarial imitation learning, Advanced Engineering Informatics 58 (2023) 102140.

[15] Y. Sun, I. Jeelani, M. Gheisari, Safe human-robot collaboration in construction: A conceptual perspective, Journal of Safety Research (2023).

[16] Y. Liu, M. Habibnezhad, H. Jebelli, Brainwave-driven human-robot collaboration in construction, Automation in Construction 124 (2021) 103556.

[17] L.P. Kaelbling, M.L. Littman, A.W. Moore, Reinforcement learning: A survey, Journal of artificial intelligence research 4 (1996) 237-285.

[18] A.S. Polydoros, L. Nalpantidis, Survey of model-based reinforcement learning: Applications on robotics, Journal of Intelligent & Robotic Systems 86 (2) (2017) 153-173.

[19] J.A. Russell, A. Weiss, G.A. Mendelsohn, Affect grid: a single-item scale of pleasure and arousal, Journal of personality and social psychology 57 (3) (1989) 493.

[20] J. Wang, P.-C. Liao, Re-thinking the mediating role of emotional valence and arousal between personal factors and occupational safety attention levels, International Journal of Environmental Research and Public Health 18 (11) (2021) 5511.

[21] M. Morikawa, Who are afraid of losing their jobs to artificial intelligence and robots? Evidence from a survey, GLO Discussion Paper, 2017.

[22] A. Weidemann, N. Rußwinkel, The Role of Frustration in Human–Robot Interaction–What Is Needed for a Successful Collaboration?, Frontiers in psychology (2021) 707.