Improving Workers' Musculoskeletal Health During Human-Robot Collaboration Through Reinforcement Learning

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Objective: This study aims to improve workers' postures and thus reduce the risk of musculoskeletal disorders in human-robot collaboration by developing a novel model-free reinforcement learning method.

Background: Human-robot collaboration has been a flourishing work configuration in recent years. Yet, it could lead to work-related musculoskeletal disorders if the collaborative tasks result in awkward postures for workers.

Methods: The proposed approach follows two steps: first, a 3D human skeleton reconstruction method was adopted to calculate workers' continuous awkward posture (CAP) score; second, an online gradient-based reinforcement learning algorithm was designed to dynamically improve workers' CAP score by adjusting the positions and orientations of the robot end effector.

Results: In an empirical experiment, the proposed approach can significantly improve the CAP scores of the participants during a human-robot collaboration task when compared with the scenarios where robot and participants worked together at a fixed position or at the individual elbow height. The questionnaire outcomes also showed that the working posture resulted from the proposed approach was preferred by the participants.

Conclusion: The proposed model-free reinforcement learning method can learn the optimal worker postures without the need for specific biomechanical models. The data-driven nature of this method can make it adaptive to provide personalized optimal work posture.

Application: The proposed method can be applied to improve the occupational safety in robot-implemented factories. Specifically, the personalized robot working positions and orientations can proactively reduce exposure to awkward postures that increase the risk of musculoskeletal disorders. The algorithm can also reactively protect workers by reducing the workload in specific joints.

Keywords: robotics, computer-supported collaborations, human-automation interaction, job risk assessment, human-robot interaction

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INTRODUCTION

Musculoskeletal disorders (MSDs) are one of the most common occupational injuries in the industry (Kang et al., 2014; Stack et al., 2016). The major causes of MSDs include repetitive motions, awkward postures (Keyserling et al., 1992), and excessive force exertion (Stack et al., 2016). In 2017, approximately 273,000 day-away-from-work cases due to MSDs were reported in the U.S. (U.S. Bureau of Labor Statistics, 2020). One way to relieve workers from repetitive tasks and excessive force exertion is to adopt industrial robots (Gualtieri et al., 2021). For example, a variety of robots have been designed to transport heavy parts for human workers (Realyvásquez-Vargas et al., 2019; Vysocky & Novak, 2016), and consequently can help reduce the risk of low-back MSDs. Nevertheless, not all the tasks can be performed by robots alone. Some still require the inputs from human workers for quality control purposes, especially in advanced manufacturing and assembly (Bi et al., 2021; Pérez et al., 2020). This human-assisted work configuration is referred to as human-robot collaboration (HRC).

Yet, the risk of MSDs can still persist in HRC tasks. When robots are pre-programmed to work at a predetermined position, this position may not accommodate all workers due to individual differences such as body dimensions (Figure 1), preferences, and other personal characteristics. As a result, without customization, HRC can cause workers to adopt awkward postures and thus increase the risk of MSDs. (Anita et al., 2014). Specifically, awkward postures are defined as excessive joint bending and twisting outside a comfortable range of motion (Jaffar et al., 2011).

To reduce the risk of MSDs during HRC, the position of robot end effector should be adaptive and lead to a neutral posture for workers. To

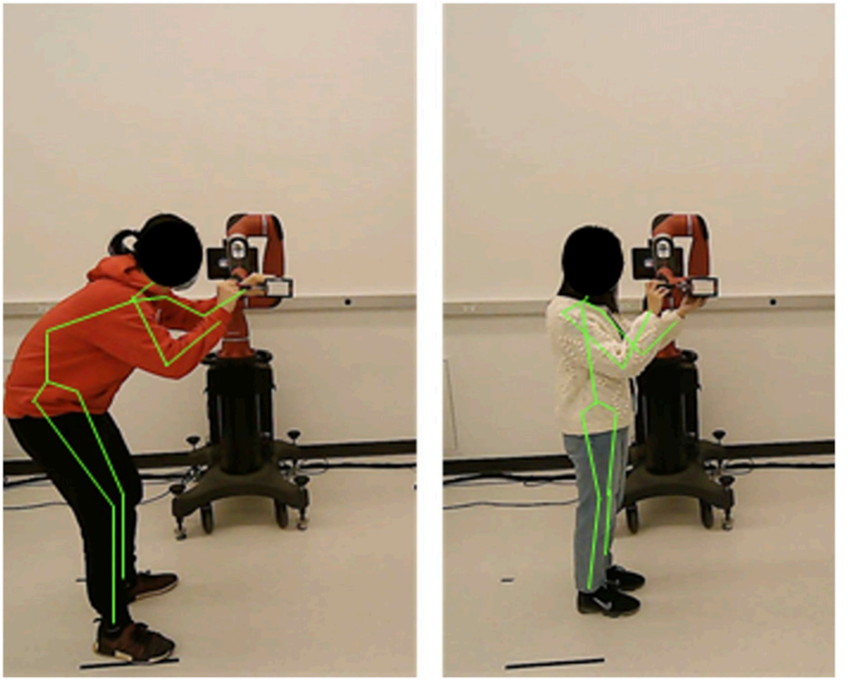


Figure 1. A set position may not be suitable for workers with different body features. A taller worker (left) has to bend forward compared to a shorter worker (right) for the same HRC task.

date, a number of optimization methods have been proposed to improve workers' postures during HRC by adjusting the position of robots' end effectors. Some studies have developed optimization methods based on joint loadings estimated through a biomechanical model or measured from electromyography (EMG) feedback (Kim et al., 2017; Peternel et al., 2017, 2018; van der Spaa et al., 2020). Yet, the estimated joint loading can be affected by the validity of the adopted biomechanical models. In some other studies (Busch et al., 2017, 2018; Roveda et al., 2020), optimizations are made to ergonomic assessment indicators. For example, Rapid Upper Limb Assessment (RULA) was used in a recent study as an indicator of workers' postural health during HRC (Liau & Ryu, 2020). RULA is a widely used and validated ergonomic tool in evaluating the overall MSD risks (Kee, 2020, 2021; McAtamney & Corlett, 1993; Micheletti Cremasco et al., 2019). A greater RULA score indicates a greater risk of developing MSD.

Traditionally, assessment and calculation of RULA postural scores require safety practitioners to manually code body postures. This process can be time-consuming and requires ergonomic expertise. In previous studies, researchers sought to improve this process by using wearable inertial measurement units (IMUs) to track workers' body postures and estimate the ergonomic score to optimize the position of a robot's end effector and improve workers' postures (Busch et al., 2017, 2018). Nevertheless, wearable sensors may not be suitable in certain field applications because they may interfere worker's natural body motion during work. An alternative way to track body motion and automatically assess RULA score is to use camera and computer vision (Li & Xu, 2019; Manghisi et al., 2017; Massiris Fernández et al., 2020; Yazdani et al., 2021). Compared with IMUs, computer vision requires a camera set nearby a working area with good field of vision and an adequate computational power for pose reconstruction. On the other hand, computer vision does not require multiple IMU sensors attached on workers' body and thus does not interfere with workers' natural body motion. Considering the scenario of HRC, different workers may work with the same collaborative robot at different time in a day. Therefore, we chose computer vision to reconstruct each worker's pose and assess the corresponding postural score modified from RULA. Otherwise, the HRC task could be interrupted by mounting IMU sensors on workers' body.

Once workers' ergonomics assessment scores are computed, different optimization algorithms can be applied to adjust positions of robots' end effector with an objective of minimizing workers' ergonomic assessment risk. Previous studies have proposed optimization methods where the ergonomic assessment was performed using simulated human pose during HRC tasks (Busch et al., 2017, 2018; Yazdani et al., 2021). However, simulation of human postures can be an ill-posed problem (Qu & Nussbaum, 2008) because 1) human body has a substantial amount of redundant degree of freedoms and 2) the range of motion limits may vary from person to person (Park et al., 2010).

In the current study, we will develop a novel model-free reinforcement learning (RL) method called Gradient-based Online Learning Algorithm in HRC (GOLA-HRC) to address these issues. This method is suitable in HRC tasks because the robot end effector can be programed to reach different positions from task to task, and from cycle to cycle. In contrast, a traditional workstation in automation only provides a fixed work position for workers. Even this position can be adjusted through ergonomics intervention, such adjustment is not as flexible as the movement of a robot end effector in an HRC task. This algorithm follows a trial-and-error method (Kober et al., 2013; Sutton & Barto, 2018) and optimizes workers' awkward posture scores obtained from computer vision without the need for a whole-body biomechanical model. The data-driven nature of the proposed method allows the robot to "learn" the optimal effector position and provide personalized configurations for individual worker. Prior to this study, RL methods have been applied in robot action planning in different scenarios (Degris et al., 2012; Haarnoja et al., 2018, 2018b; Hu et al., 2019) and these applications exhibit promising potential in optimization tasks. The rest of this paper is organized as follows: the method section describes the adopted computer vision method, the automated postural assessment technique, the proposed GOLA-HRC algorithm, and the experiment design for algorithm validation. The result section shows the validation outcomes. The discussion section discusses the key findings of this research, current limitations, and future works.

METHOD

Automated Continuous Awkward Posture Score Estimation

Worker Posture Reconstruction. The initial step is to equip the robot with the ability to determine the risk level of a worker's posture. To accomplish this, workers' postures are first estimated with a computer vision model and the images collected from a single RGB camera. Specifically, the open-source computer vision model named VideoPose3D model (Pavllo et al., 2019) is used to predict 3D key joint positions of a worker based on frames captured by the camera (Figure 2). One advantage of the 3D computer vision model is that it allows for the analysis of off-plane movements, such as shoulder abduction. The mean absolute error of the estimated joint positions is reported to be 46.8 mm (Pavllo et al., 2019). Subsequently, the estimated joint positions are utilized to compute the relevant awkward posture score.

Continuous Awkward Posture Score. Traditional RULA assessment evaluates overall scores of workers' postures by grouping the body part posture scores. The body part posture scores are step functions which are less sensitive when body joint angles are in the same category. For instance, trunk forward bending angles at 25° and 60° are treated as having the same body part score. Such a feature limits algorithms to find the optimization direction since there would be no gradient on RULA score. Thus, we propose to fit body part RULA postural scores into a continuous linear function (Figure 3), which is referred as continuous award posture (CAP)

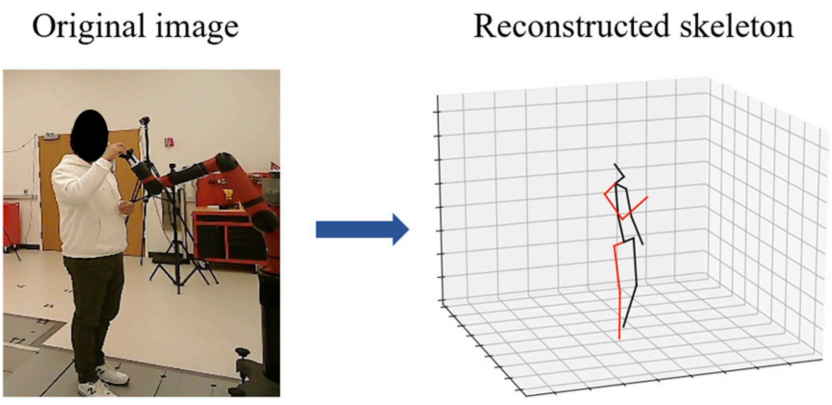


Figure 2. The workflow of worker pose reconstruction. An RGB camera first captures an image of the workspace. The computer vision model then reconstructs the worker's pose.

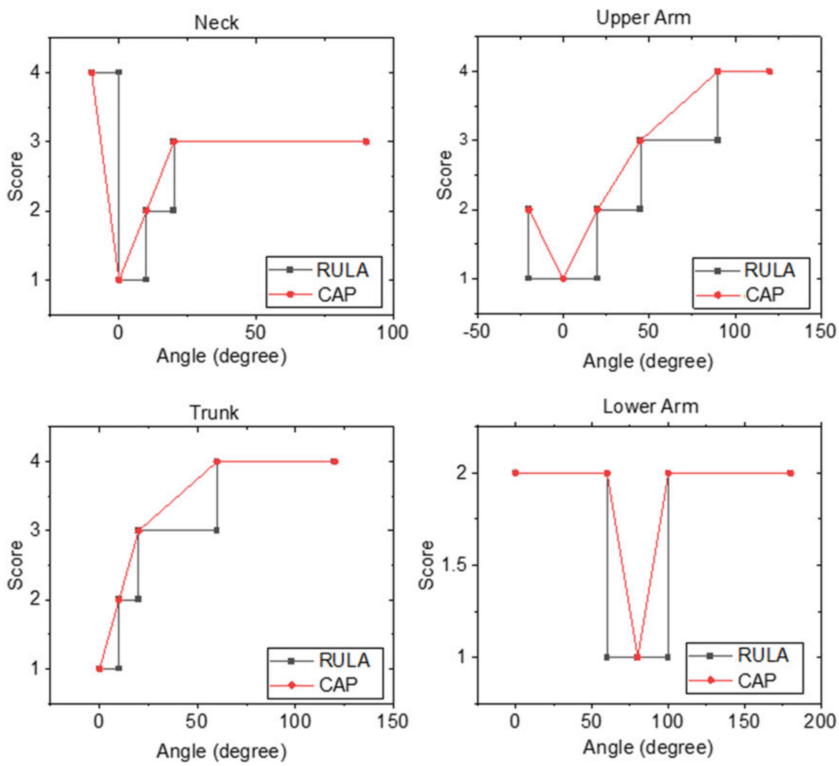


Figure 3. Comparison of body part RULA postural score and the proposed CAP scores of the neck, upper arm, trunk, and lower arm.

score hereinafter. This approach provides several benefits. The gradient of a linear function is constant, which helps stabilize the learning process, and the continuous nature of the CAP score allows for more precise optimization of workers' postures. In addition, it is important to note that we add a penalizing score of four to CAP whenever the workers' knee angle is over 20° to penalize deep squatting postures. This penalizing score can also be implemented as a linear function. The joint scores are then summed with equal weighting factors to form the overall CAP score, which is used in the downstream reinforcement learning algorithm.

Gradient-Based Online Learning Algorithm in HRC

Collaboration Tasks. An HRC task was designed as a testbed for the development of the GOLA-HRC method. In this task, participants were asked to perform a fine wire insertion task where they were instructed to insert wires into a specific position on a breadboard gripped by a collaborative robot (Sawyer, Rethink Robotics). This task simulated a common human-assisted assembly task.

Robot Degree of Freedom to Adjust. During the collaboration, workers' postures can be affected by the position and orientation of the robot's end effector. The adopted robot's end effector has six degrees of freedom (DoF), including three translational DoF (x, y, z, shown in Figure 4) and three rotational DoF (α, β, γ, Figure 4). Therefore, one can adjust the value of these six DoFs to affect workers' CAP scores. To reduce the state space (number of variables) and improve learning speed, some variables that are less likely to affect workers' posture (as workers can move in these directions freely) are excluded in this study. Specifically, participants were encouraged to freely move during the experiment. Therefore, horizontal translational motions of the end effector (x and z) are less likely to affect workers' postures and could be excluded for the purpose of dimension reduction. Similarly, the rotational motion along the β-axis could be compensated by the horizontal movement of workers. In addition, the rotational motions along the γ-axis do not affect workers' postures due to the nature of the adopted fine wire insertion task, Therefore, there are two remained degree of freedom that can be adjusted for alternating workers' posture: the translational motion along the y-axis, which determines the height of the end effector, and the rotational motion along the α-axis, which determines the pitch angle of the end effector. The rest of the DoFs remain the same throughout the experiments.

RL Algorithm. The proposed GOLA-HRC algorithm searches for a set of values of the abovementioned DoF that minimizes the CAP score of a worker. The flowchart and algorithm are shown in Figure 5. With the computer vision, each time a worker finishes a fine wire insertion task at given end effector position and orientation, a robot posture-CAP score pair is generated (Figure 5). The gradient indicating the optimization direction (Bottou, 2012; Duchi et al., 2011) can be then calculated by the robot posture-CAP pair. Following the gradient, the GOLA-HRC iterates until the termination conditions are met.

The gradients of CAP corresponding to the position changes along y-axis and orientation changes with respect to x-axis at each time step, ∇_{t_p} and ∇_{t_o}, are defined in equation (1) and (2). These gradients indicate how the CAP can be improved or deteriorated by a translational motion or a rotational motion. Using the gradient, the end effector position and orientation at step t + 1 (P_{t+1} and O_{t+1}) are determined by the previous end effector position and orientation at time t (P_t and O_t) as well as the respective search step lengths (δh and δa) as described in Equation (3) ~ (6). In equation (3) ~ (4), l_p and l_o are the learning rates set for adjusting the position and the orientation. We impose constraints s_p and s_o on the step lengths to guarantee a stable search process. A discount factor (d_α) is introduced to control the learning rate dynamically as a common practice in reinforcement learning (Sutton & Barto, 2018). A greater discounting factor improves the optimization accuracy but also increases the number of iterations. Learning rates l_p and l_o evolve after each iteration according to Equation (7) ~ (8). A termination condition is a predefined criterion that, when met, signals the end of the iteration process (Sutton & Barto, 2018). In this study, the termination condition is defined in equation (9), where ϵ is an error parameter that represents a tradeoff between convergence speed (i.e., how fast algorithm reaches optimal) and solution precision.

Note that the GOLA-HRC algorithm includes a set of initialization parameters ($\delta h_0, \delta a_0, l_{p0}, l_{o0}, P_0, O_0$) and hyper-parameters ($s_p, s_o, d_\alpha, \epsilon$) that constrain the behavior of the

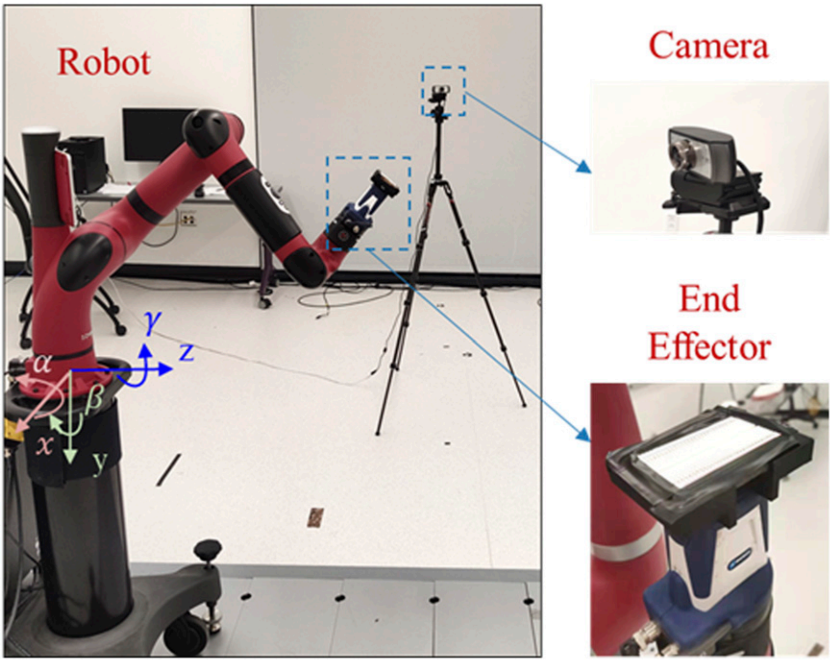
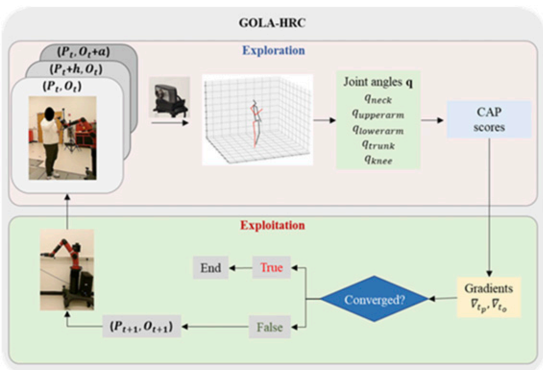


Figure 4. The collaborative task: A camera is placed three m away from the collaborative robot. The origin of the robot coordinate system is set on the robot base. The directions of translational axes x, y, and z and rotational axes $\alpha, \beta, and\, \gamma$ are shown.



Algorithm: GOLA-HRC

Input: initial position and orientation P_0, O_0; searching search step lengths h_0, a_0; step limits s_p, s_o; learning rates l_p, l_o; discounting factor α

set $P = P_0$, O= O_0 move end effector to (P, O).

for t = 0,1,2,……,N **do**

set $P_t = P_{t-1} + h_t, O_t = O_{t-1} + a_t$

Move to (P_t, O_t). Record CAP_t;

Move to $(P_t + h_t, O_t)$, record CAP_t^p;

Move to $(P_t, O_t + a_t)$, record CAP_t^o;

$\nabla_{t_p} = (CAP_t^p - CAP_t)/h_t$,

$\nabla_{t_o} = (CAP_t^o - CAP_t)/a_t$;

if $|\nabla_{t_p}| < \epsilon\, and\, |\nabla_{t_o}| < \epsilon$ **then**:

end loop

$h_{t+1} = min\left(l_p \cdot \nabla_{t_p}, s_p\right) \cdot \frac{\nabla_{tp}}{|\nabla_{tp}|}$,

$a_{t+1} = min(l_o \cdot \nabla_{t_o}, s_o) \cdot \frac{\nabla_{to}}{|\nabla_{to}|}$;

$l_p = \alpha \cdot l_p, l_o = \alpha \cdot l_o$

Figure 5. Gradient-based online learning algorithm in HRC (GOLA-HRC). Left: flow chart of GOLA-HRC. Right: the algorithm pseudocode.

searching process, which is the nature of machine-learning algorithms (Yang & Shami, 2020). Initialization parameters are default values of the variables when the system initializes and are set before the training begins. The hyper-parameters define the behavior of the algorithm, such as how data is loaded (Snoek et al., 2012). In this study, hyper-parameters are manually initialized based on our previous experiences in computer vision and reinforcement learning. A grid search protocol was then adopted for tuning the hyper-parameters to improve the performance and convergence speed. Specifically, the termination threshold ϵ

should be carefully determined. If the value of ϵ is excessively small, the learning process may not terminate, as there may be intra-individual posture variations even when the end effector remains in the same position. Such posture difference can introduce a certain level of noise to the gradients. On the other hand, when ϵ is greater, the algorithm converges faster but yields a less accurate solution. The initialization parameters are based on anthropometric data. Specifically, initial end effector position in the y-axis direction and orientation with respect to x-axis direction were set to 1.055 m and 0°. With this setting, the breadboard is placed at the 50% ile elbow height of the entire population (male and female combined) (Freivalds & Niebel, 2008). The reason we choose the elbow height is that it is considered as a preferred height for assembly tasks in terms of reducing MSD risks (Freivalds & Niebel, 2008). The initial search step lengths were set as $\delta h_0 = 0.15m$ and $\delta a_0 = 20°$, and the initial learning rates were set as $l_{p0} = 1.1$ and $l_{o0} = 1.1$. These values were determined in a preliminary test for an adequate convergence speed. The values of the tuned hyper-parameters and initialization parameters are described in Table 1

$$\nabla_{t_p} = \left(CAP_t^p - CAP_t\right) / \delta h \tag{1}$$

$$\nabla_{t_o} = \left(CAP_t^o - CAP_t\right) / \delta a \tag{2}$$

$$\delta h = \min\left(l_p \cdot |\nabla_{t_p}|, s_p\right) \cdot \frac{\nabla_{t_p}}{|\nabla_{t_p}|} \tag{3}$$

$$\delta a = \min(l_o \cdot |\nabla_{t_o}|, s_o) \cdot \frac{\nabla_{t_o}}{|\nabla_{t_o}|} \tag{4}$$

$$P_{t+1} = P_t + \delta h \tag{5}$$

$$O_{t+1} = O_t + \delta a \tag{6}$$

$$l_p = d_\alpha \cdot l_p \tag{7}$$

$$l_o = d_\alpha \cdot l_o \tag{8}$$

$$\left|CAP_t^p - CAP_t\right| < \epsilon \text{ and } \left|CAP_t^o - CAP_t\right| < \epsilon \tag{9}$$

TABLE 1: The Values of Initialization Parameters and Hyper-Parameters

Parameters	In Equation #	Values
δh_0	1	0.15 m
δa_0	2	20°
P_0	5	1.055 m
O_0	6	0°
l_{p0}	7	1.1
l_{o0}	8	1.1
s_p	3	0.2 m
s_o	4	30°
d_α	7, 8	0.9
ϵ	9	0.3

Experiment Setup

Apparatus and Participants. As shown in Figure 4, a gripper was 3D printed and attached to the end effector (EGP-C 40, Schunk) of the collaborative robot to hold a breadboard (5.5 cm × 17 cm). The robot was connected to a workstation with a GPU (NVIDIA RTX 2080Ti) that supported the computer vision algorithms. All the computer vision algorithms, CAP score calculations, and the RL algorithm were programmed in Python (Ver. 3.6) on Linux platform (Ver. 16.04). Communication between the workstation and the robot was realized through Intera SDK (Ver. 5.3) based on Robot Operating Systems (ROS Kinetic). A webcam (Model: MF920P, Spedal) was placed three m away from the robot to capture the images of the participants and then send the images to the workstation. Twenty participants were recruited (10 males and 10 females, with an average age of 27.3 ± 2.7 years old, height of 172 ± 11 cm, weight of 73 ± 15 kg) in this study. This research is in compliance with the tenets of the Declaration of Helsinki was approved by the Institutional Review Board at North Carolina State University (#24250). Informed consent was obtained from each participant.

Experiment Process. To evaluate the effectiveness of the GOLA-HRC method, we performed a validation study. During the experiment, each participant was first asked to repetitively perform the fine wire insertion task until the estimated CAP scores converged with

ϵ. After each repetition, the position and orientation of the robot's end effector was adjusted by applying the GOLA-HRC algorithm. The final position and orientation of the end effector with the converged CAP score was referred to as "*Learnt*" position hereafter. In addition, participants' CAP scores were also investigated when the end effector was placed at the 50% ile elbow height (referred to as "*Fixed*") as well as the computer-vision captured individual elbow height (i.e., the output of the Videopose3D right elbow position, referred to as "*Elbow Height*"). The orientations of the "Fixed" and "Elbow Height" are set to be 0°, which is the same orientation as shown in Figure 6 iteration 1. Furthermore, the participants were also asked to adjust the end effector to a position that they were most comfortable with, referred to as "*Worker-selected*" positions hereafter. This position was considered the subjectively optimal positions that resulted in minimal workload risk from a psychophysical perspective (Snook & Ciriello, 1991). During the experiment, the end effector was placed in each of the above-mentioned four positions (*Learnt*, *Fixed, Elbow Height* and *Worker-selected*) with a random order. At each position, participants performed the fine wire insertion task three times and the CAP scores were calculated.

After inserting the fine wire at each tested end effector position, the participants were asked to complete a questionnaire. A questionnaire from a previous study on human-robot collaboration (Busch et al., 2017) was adopted in this study with some revisions. The participant was asked to rate whether the end effector position was appropriate from three aspects. Specifically, nine questions in "Partnership," "Performance," and "Safety" were asked. The three "Partnership" questions evaluating workers' feelings of a robot as a co-worker were: "I reckon the robot is a good co-worker," "I think the robot is not adapted to the handover task," and "I prefer to finish the task alone." The "Performance" questions examining the extent to which the robot's behavior matched the worker's expectations were: "I think the robot is trying to help me', 'I feel the robot's behavior is similar to my expectations," and "I think the robot has helped me keeping a good posture." The questions on "Safety" asking the workers to assess whether they felt the collaboration tasks were safe were: "I believe I would feel exhausted repeating this task for hours," "I feel comfortable picking up the object from the co-robot," and "I would suffer from chronic pain working with the robot every day." The Likert scale was used to quantify the response, with "0" representing "extremely disagree" and "7" representing "extremely agree."

Statistical Analysis

Nonparametric statistical tests were performed in this study considering the collected data does not follow a normal distribution ($p < 0.05$ in Shapiro-Wilk and Anderson Darling tests). Specifically, Kruskal–Wallis one-way analysis of variance was performed to investigate whether different end effector positions had significant effects on CAP and the subjective questionnaire scores. Steel-Dwass test was then performed for pairwise comparisons.

RESULTS

CAP Score vs Iterations

Figure 6 shows how the GOLA-HRC improved the working posture of a participant step by step until the end effector moves to the *Learnt* position. In this figure, the initial position was too low for the participant and resulted in a forward trunk bending posture. By calculating the gradient of the CAP score, the algorithm adjusted the position and orientation of the end effector until the CAP score converged. In average, the proposed algorithm converges after 12.4 iterations.

CAP Scores

The Kruskal–Wallis tests showed that the end effector positions had a significant impact on participants' CAP scores ($p < 0.0001$). As

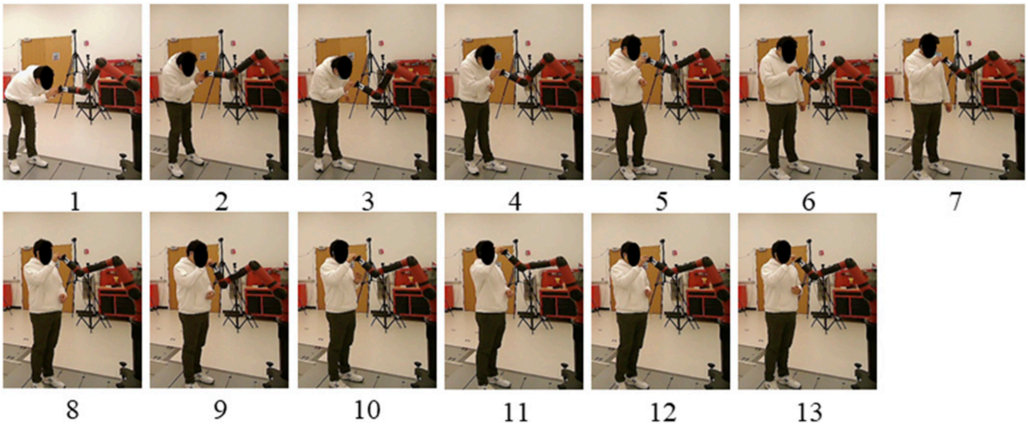


Figure 6. Postures over 13 iterations until the CAP score met the termination criterion.

depicted in Figure 7, the results of the Steel-Dwass tests indicated that there was no significant difference between the *Worker-selected* and *Learnt* positions. However, significant differences were observed in all other paired comparisons. To better understand the exposure magnitude of each individual joint, we further analyzed the CAP scores for specific body parts (Figure 7(b)). The results showed that the end effector positions had a similar effect on neck and trunk bending angles, but no significant differences were observed in lower and upper arm angles.

Subjective Rating

The results of the subjective questionnaire are presented in Figure 8, with statistical significance marked. According to the Steel-Dwass tests, there is no significant difference between the *Learnt* and *Worker-selected* positions. Similarly, there is no significant difference between the *Elbow Height* and *Fixed positions*. These findings suggest that participants did not perceive a significant difference between the *Learnt* position and the *Worker-selected* position. Additionally, the results align with the findings from the CAP measurement, indicating that the *Learnt* position is significantly more preferred than both the *Fixed* and *Elbow Height* positions. The subjective questionnaire shows that the *Fixed* and *Elbow Height* positions have a similar effect on workers' perceptions, which differs from the CAP results.

DISCUSSIONS

Effectiveness of GOLA-HRC

As shown in the Results, the overall CAP scores of the *Learnt* positions are significantly smaller than those of the *Fixed* positions and *Elbow Height* positions. This result indicates that the GOLA-HRC can effectively improve the posture of a worker and thus reduce the MSD risks. Also, it was found that the CAP scores of *Elbow Height* positions are significantly lower than the CAP scores of the Fixed positions, which indicates individualizing the robot end effector position helps improve the worker's posture.

When the performances of *Learnt* positions were further compared with the *Worker-selected* positions, it was found that there is no significant difference on CAP. A closer look on each component of CAP score further revealed that the effects of different end effector positions are more significant for the "Neck" score and "Upper Arm" score (Figure 6b). Particular, *Worker-selected* and *Learnt* positions significantly reduced neck flexion/extension angles and shoulder-elevation angles.

Such a result suggests that GOLA-HRC algorithm is able to converge at the positions that match the positions selected by

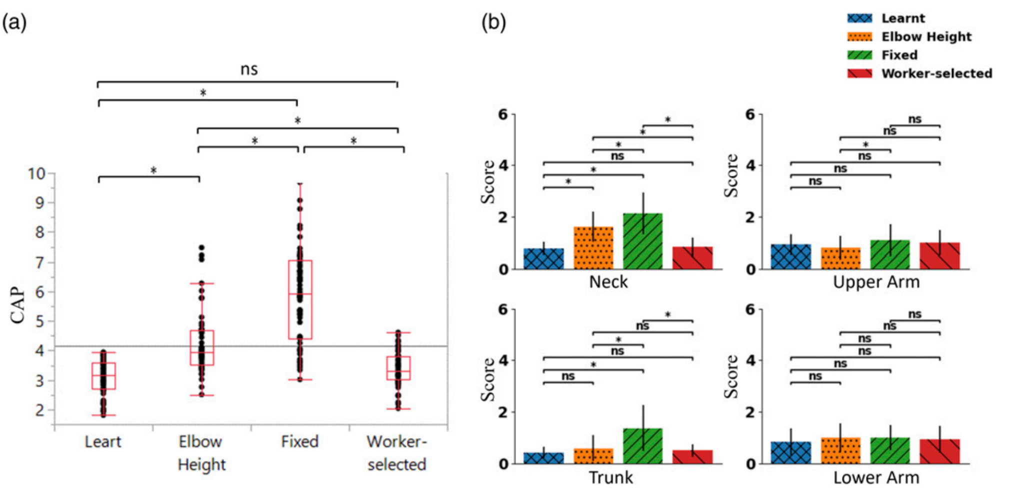


Figure 7. (a) Means and quantiles of CAP score corresponding to different end effector positions. The red box plots show the 90%, 75%, 50%, 25%, 10% quantiles. The gray horizontal line indicates the overall average value of CAP scores across all experimental trials. (b) Means and standard deviation of CAP scores of specific body joint angles. The results of are annotated: "ns"—no significance; "*"—$p < .05$.

workers. Meanwhile, there is no significant difference between *Learnt* and *Worker-selected* positions in any subjective ratings, which indicates that the *Learnt* position introduces the same level of physical workload as the baseline *Worker-selected* position. As the *Worker-selected* position is subjectively selected by the participants, this position can be considered as the optimal position from the psychophysical perspective (Snook & Ciriello, 1991). In psychophysics, it is assumed that people have the ability to be "self-protecting" from musculoskeletal injury by adopting relatively safe working postures and safe lifting weight (Acevedo & Ekkekakis, 2006). While this assumption has been challenged on the basis that workers, particularly new employees lacking sufficient training, may have difficulty in accurately gauging the actual risks involved, psychophysics approaches have been utilized in ergonomics interventions (Fernandez & Marley, 2014; Jiang et al., 1986).

Adaptability of GOLA-HRC

During the experiment, a postural difference among participants was visually observed by the experimenters. For example, some people tended to move their eyes and kept their necks straight during the tasks (Figure 9 left), while others tended to make neck flexions and gazed toward the breadboards without moving their eyes much (Figure 9 right). Yet, it should be noted our proposed GOLA-HRC algorithm would converge at a higher position for the participants who tend to bend their neck to a greater extent. This is because the algorithm is more sensitive to the neck angles than the height of the breadboard. Another finding is that the optimized end effector orientation always points to the face of the participants since otherwise participants would have to greatly squat or bend their neck to look at the breadboard.

Safety Awareness of Workers in HRC

As collaborative robots have been newly adopted in recent years, limited research has been done in workers' safety awareness of long-term human-robot interaction. In particular, it is unclear whether the subjectively optimal position (i.e., "worker-selected" position) is equivalent to the CAP-based optimal position. As described in the previous section, some participants have a significant neck flexion when they look at the breadboard, and therefore the GOLA-HRC algorithm moves the end effector

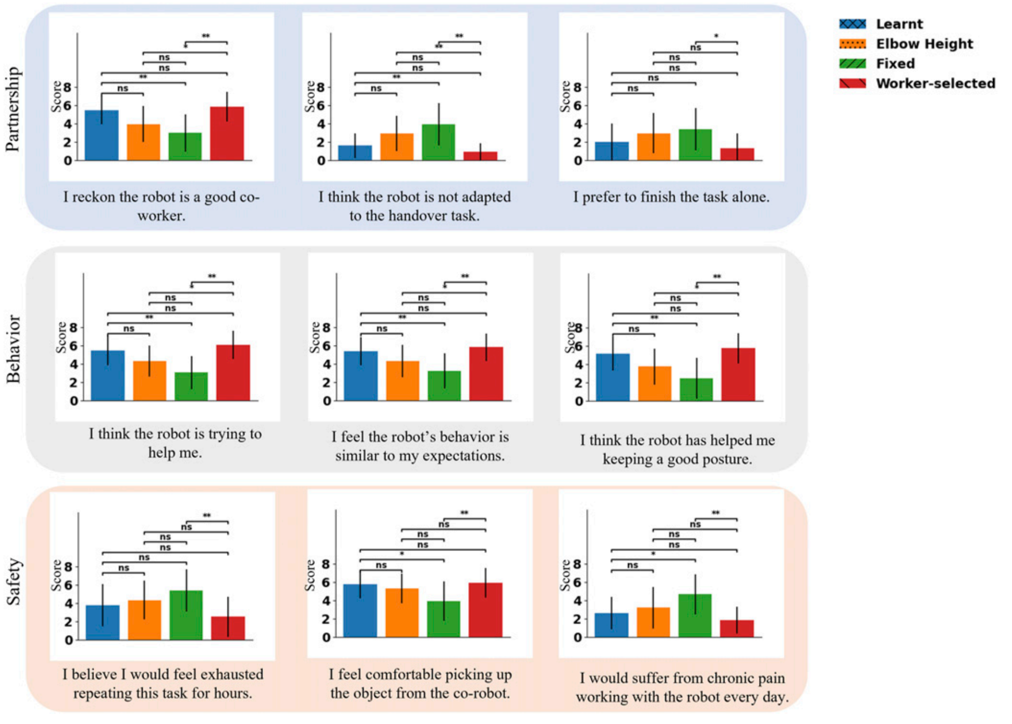


Figure 8. Summary of the questionnaire. The questionnaire includes three aspects "Partnership," "Behavior," and "Safety," and each of them is evaluated by three questions. The questions were randomized, and the participants did not know the aspects when they were answering the questions. The Likert scale was used to quantify the response, with "0" representing "extremely disagree" and "7" representing "extremely agree." The results of Steel-Dwass tests are annotated: "ns"—no significance; "*"—$p < .05$.

to higher positions to prevent high scores of the neck. According to the experiment, the majority of the participants (17 out of 20) did adjust the end effector to a position where they have a more neutral neck angle when they were asked to adjust the end effector positions. Yet, three participants selected a position with a greater neck flexion angle (Figure 10). For the participants in Figure 10, the *Worker-selected* position is below the worker's shoulder, which prevents the flexion of the upper arm but results in a greater neck flexion angle. The reason for choosing a posture with a greater neck flexion could be that some participants have personal preferences on a smaller shoulder flexion. While such a posture may not result in any discomfort over a short term, it may eventually lead to MSDs over a long period of time. Therefore, if workers are able to select the working location in an HRC task, ergonomics education is still necessary to ensure that they do not choose a posture that poses risk of MSDs on a specific joint.

Personalization of CAP

One advantage of the proposed model-free RL method is that the optimization criteria can be conveniently personalized for workers by assigning different weighting factors to each joint, which can be helpful for individualized safety considerations. For instance, workers who already experience neck discomfort should ensure their neck is in an as much neutral posture as possible. In that case, one can apply a greater weighting factor to the "Neck" CAP score before applying the RL algorithm. In a preliminary test, the robot's end effector moved to a higher

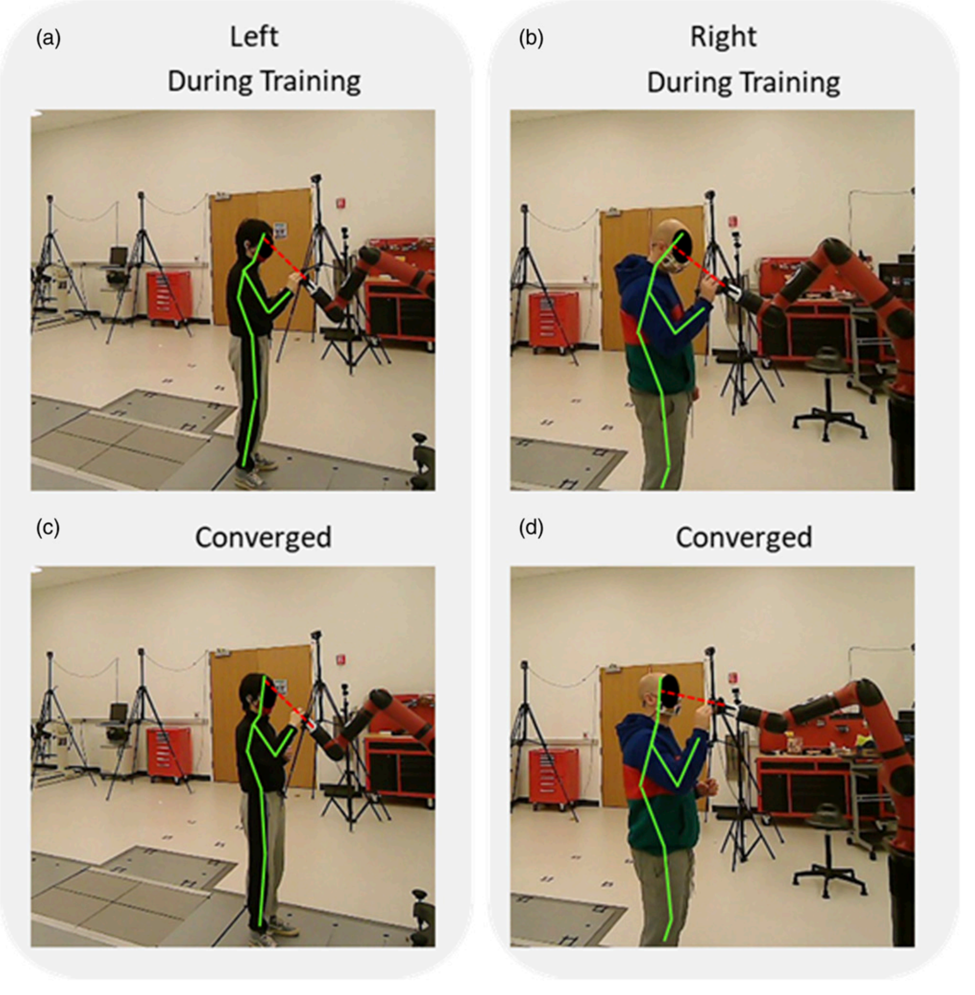


Figure 9. The postures of workers gazing behavior. The white lines are reconstructed skeletons and gray dashed lines indicate the sight of the workers' eyes. The eyesight lines are closer to be vertical to the head skeleton lines in (b) and (d).

position when the weighting factor of 'Neck' is doubled and thus resulting in a smaller neck flexion angle but a greater arm elevation angle (Figure 11). Similarly, we can easily modify the weighting factors of other joints to personalize the GOLA-HRC algorithm for specific needs. In this way, we can proactively prevent workers from injuring a specific joint or reactively help workers avoid awkward posture of a joint with chornic pain. Another advantage of GOLA-HRC is its flexibility in applications. There are various ergonomic accessment tools, such as REBA (Hignett & McAtamney, 2000) and NERPA (Sanchez-Lite et al., 2013) that show a variety of performance in different job configurations (Yazdanirad et al., 2018). The reward function of GOLA-HRC can be easily modified to fit other ergonomic assessment tools. Moreover, the overall CAP score in the current study is a linear summation of the CAP scores of each body part of a worker. If more evenly distributed scores among each joint are preferred, one can choose square or cubic summation which would penalize greater sub-scores.

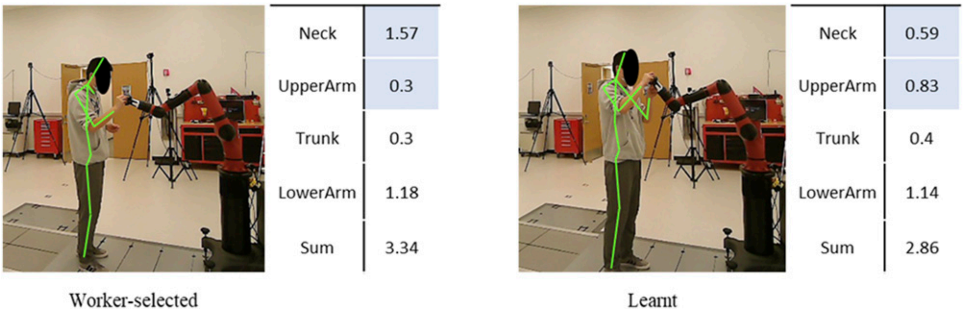


Figure 10. A worker's postures in *Learnt* and *Worker-selected* positions. The *Worker-selected* position poses greater risk on the neck, while the *Learnt* position balanced the "Neck" and "Upper Arm" CAP scores.

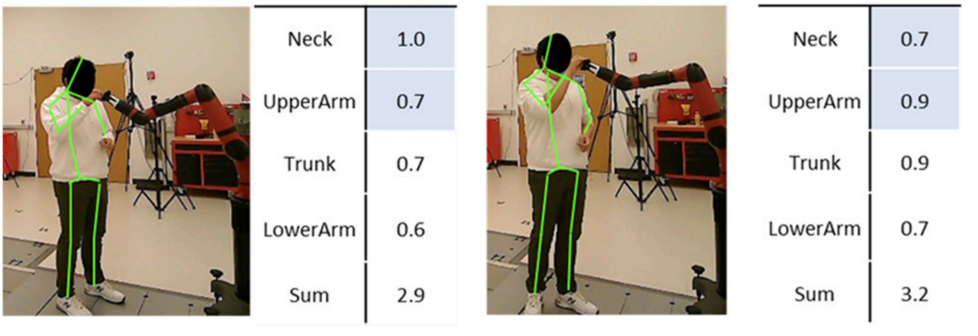


Figure 11. Left: The optimized posture in original CAP. Right: The optimized posture with doubled weight on neck angle.

Limitations

There are a number of limitations that need to be addressed. First, the optimization process in the current study only considered two degrees of freedom of the robot end effector. In a real-world setting, a human-robot collaboration task can be more complicated and thus more robot end effector degree of freedom may need to be optimized. With a greater number of the degree of freedom to optimize, the state space, however, will exponentially grow. One possible solution is using sequential learning, which divide one complex problem with multiple parameters into several problems with fewer parameters, but the validity of sequential learning needs further investigation. Second, since the computer vision algorithm was used for pose reconstruction in this study, a camera needs to be placed where its field of view is not blocked. Otherwise, the error in pose reconstruction will be greater. To address this problem, one could consider using a multi-camera computer vision system. In addition, it was found that the output of the computer vision model could be less precise on worker's neck angle when the hair blocks the view of their neck. A headband may be needed for workers with longer hair. Third, the error in the reconstructed joint position can affect the value of the calculated CAP. To what extent this error affects the CAP score needs to be further investigated. On the other hand, we found the magnitude and the direction of the joint position error are not substantially affected by human postures. Thus, the gradient calculated in GOLA-HRC is less affected by this error as the gradient is calculated by the difference of CAP between each iteration. Fourth, worker's loose clothes may occlude certain visual features for a precise human pose reconstruction. As suggested by a previous study (Liang & Lin, 2019), a multimodal database including the images of workers wearing a variety clothes as well as the ground-truth joint positions are further needed for training a more robust computer-vision algorithm. Fifth, the participants recruited in this study are not required to have professional work experience in HRC. Therefore, the postures adopted by these participants may differ from those of actual workers. Whether HRC-related working experiences affect the performance of the proposed method should be further examined.

CONCLUSION

In this study, we proposed a method to optimize workers' posture during HRC. A computer vision method was first adopted to recognize human posture and determine a CAP score. A model-free gradient descent optimization algorithm was then developed to lower the CAP score of a worker. The experimental result shows that GOLA-HRC effectively lowers workers' CAP during HRC tasks and thus reducing exposure to postural risk factors of MSDs.

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KEY POINTS

- A reinforcement learning algorithm, GOLA-HRC, was developed to reduce exposure to postural risk factors for MSDs.
- The algorithm was integrated with a computer vision method and validated in a laboratory-based experiment. Results showed the proposed approach is effective to improve the working posture of the participants.
- The data-driven nature of this approach can make it adaptive to provide personalized optimal work posture.

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REFERENCES

Acevedo, E. O., & Ekkekakis, P. (2006). *Psychobiology of physical activity* (1st ed.). Human Kinetics.

Anita, A. R., Yazdani, A., Hayati, K. S., & Adon, M. Y. (2014). Association between awkward posture and musculoskeletal disorders (MSD) among assembly line workers in an automotive industry.

Bi, Z. M., Luo, C., Miao, Z., Zhang, B., Zhang, W. J., & Wang, L. (2021). Safety assurance mechanisms of collaborative robotic systems in manufacturing. *Robotics and Computer-Integrated Manufacturing*, *67*, 102022. https://doi.org/10.1016/j.rcim.2020.102022.

Bottou, L. (2012). Stochastic gradient descent tricks. In *Neural networks: Tricks of the trade* (pp. 421–436). Springer.

Busch, B., Maeda, G., Mollard, Y., Demangeat, M., & Lopes, M. (2017). Postural optimization for an ergonomic human-robot interaction. 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Vancouver, BC, Canada, 24-28 September 2017, pp. 2778–2785.

Busch, B., Toussaint, M., & Lopes, M. (2018). Planning ergonomic sequences of actions in human-robot interaction. 2018 IEEE International Conference on Robotics and Automation (ICRA), Brisbane, QLD, Australia, 21-25 May 2018, pp. 1916–1923.

Degris, T., Pilarski, P. M., & Sutton, R. S. (2012). Model-free reinforcement learning with continuous action in practice. 2012 *American Control Conference (ACC), Fairmont Queen Elizabeth in Montréal*, 27-29 June 2012, pp. 2177–2182.

Duchi, J., Hazan, E., & Singer, Y. (2011). Adaptive subgradient methods for online learning and stochastic optimization. *Journal of Machine Learning Research*, *12*(7). https://dl.acm.org/doi/10.5555/1953048.2021068.

Fernandez, J. E., & Marley, R. J. (2014). The development and application of psychophysical methods in upper-extremity work tasks and task elements. *International Journal of Industrial Ergonomics*, *44*(2), 200–206. https://doi.org/10.1016/j.ergon.2012.09.004

Freivalds, A., & Niebel, B. W. (2008). Niebel's Methods, Standards, and Work Design.

Gualtieri, L., Rauch, E., & Vidoni, R. (2021). Emerging research fields in safety and ergonomics in industrial collaborative robotics: A systematic literature review. *Robotics and Computer-Integrated Manufacturing*, *67*, 101998. https://doi.org/10.1016/j.rcim.2020.101998.

Haarnoja, T., Ha, S., Zhou, A., Tan, J., Tucker, G., & Levine, S. (2018a). Learning to walk via deep reinforcement learning. *ArXiv Preprint ArXiv:1812.11103*.

Haarnoja, T., Pong, V., Zhou, A., Dalal, M., Abbeel, P., & Levine, S. (2018b). Composable deep reinforcement learning for robotic manipulation. 2018 IEEE International Conference on Robotics and Automation (ICRA), Brisbane, QLD, Australia, 21-25 May 2018, pp. 6244–6251.

Hignett, S., & McAtamney, L. (2000). Rapid entire body assessment (REBA). *Applied Ergonomics*, *31*(2), 201–205. https://doi.org/10.1016/s0003-6870(99)00039-3

Hu, B., Shao, S., Cao, Z., Xiao, Q., Li, Q., & Ma, C. (2019). Learning a faster locomotion gait for a quadruped robot with model-free deep reinforcement learning. 2019 IEEE International Conference on Robotics and Biomimetics (ROBIO), pp. 1097–1102.

Jaffar, N., Abdul-Tharim, A. H., Mohd-Kamar, I. F., & Lop, N. S. (2011). A literature review of ergonomics risk factors in construction industry. *Procedia Engineering*, *20*, 89–97. https://doi.org/10.1016/j.proeng.2011.11.142.

Jiang, B. C., Smith, J. L., & Ayoub, M. M. (1986). Psychophysical modelling for combined manual materials-handling activities. *Ergonomics*, *29*(10), 1173–1190. https://doi.org/10.1080/00140138608967233

Kang, D., Kim, Y.-K., Kim, E.-A., Kim, D. H., Kim, I., Kim, H.-R., Min, K.-B., Jung-Choi, K., Oh, S.-S., & Koh, S.-B. (2014). Prevention of work-related musculoskeletal disorders. *Annals of Occupational and Environmental Medicine*, *26*(10), 1–2. Springer.

Kee, D. (2020). An empirical comparison of OWAS, RULA and REBA based on self-reported discomfort. *International journal of occupational safety and ergonomics: JOSE*, *26*(2), 285–295. https://doi.org/10.1080/10803548.2019.1710933

Kee, D. (2021). Comparison of OWAS, RULA and REBA for assessing potential work-related musculoskeletal disorders. *International Journal of Industrial Ergonomics*, *83*, 103140. https://doi.org/10.1016/j.ergon.2021.103140.

Keyserling, W. M., Brouwer, M., & Silverstein, B. A. (1992). A checklist for evaluating ergonomic risk factors resulting from awkward postures of the legs, trunk and neck. *International Journal of Industrial Ergonomics*, *9*(4), 283–301. https://doi.org/10.1016/0169-8141(92)90062-5

Kim, J., An, J. U., Kim, W., Lee, S., & Cho, S. (2017). Differences in the gut microbiota of dogs (*Canis lupus familiaris*) fed a natural diet or a commercial feed revealed by the Illumina MiSeq platform. *Gut pathogens*, *9*(1), 68–75. https://doi.org/10.1186/s13099-017-0218-5

Kober, J., Bagnell, J. A., & Peters, J. (2013). Reinforcement learning in robotics: A survey. *The International Journal of Robotics Research*, *32*(11), 1238–1274. https://doi.org/10.1177/0278364913495721

Li, L., & Xu, X. (2019). A deep learning-based RULA method for working posture assessment. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *63*(1), 1090–1094. https://doi.org/10.1177/1071181319631174

Liang, J., & Lin, M. C. (2019). Shape-aware human pose and shape reconstruction using multi-view images. Proceedings of the IEEE/CVF International Conference on Computer Vision, South Korea, 27 October 2019 – 2 November 2019, pp. 4352–4362.

Liau, Y. Y., & Ryu, K. (2020). Task allocation in human-robot collaboration (HRC) based on task characteristics and agent capability for mold assembly. *Procedia Manufacturing*, *51*, 179–186. https://doi.org/10.1016/j.promfg.2020.10.026.

Manghisi, V. M., Uva, A. E., Fiorentino, M., Bevilacqua, V., Trotta, G. F., & Monno, G. (2017). Real time RULA assessment using Kinect v2 sensor. *Applied Ergonomics*, *65*, 481–491. https://doi.org/10.1016/j.apergo.2017.02.015.

Massiris Fernández, M., Fernández, J. Á., Bajo, J. M., & Delrieux, C. A. (2020). Ergonomic risk assessment based on computer vision and machine learning. *Computers & Industrial Engineering*, *149*, 106816. https://doi.org/10.1016/j.cie.2020.106816.

McAtamney, L., & Nigel Corlett, E. (1993). RULA: a survey method for the investigation of work-related upper limb disorders. *Applied Ergonomics*, *24*(2), 91–99. https://doi.org/10.1016/0003-6870(93)90080-s.

Micheletti Cremasco, M., Giustetto, A., Caffaro, F., Colantoni, A., Cavallo, E., & Grigolato, S. (2019). Risk assessment for musculoskeletal disorders in forestry: A comparison between RULA and REBA in the manual feeding of a wood-chipper. *International Journal of Environmental Research and Public Health*, *16*(5), 793. https://doi.org/10.3390/ijerph16050793

Park, W., Ramachandran, J., Weisman, P., & Jung, E. S. (2010). Obesity effect on male active joint range of motion. *Ergonomics*, *53*(1), 102–108. https://doi.org/10.1080/00140130903311617

Pavllo, D., Feichtenhofer, C., Grangier, D., & Auli, M. (2019). 3d human pose estimation in video with temporal convolutions and semi-supervised training. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Long Beach, California, 16–20 June 2019, pp. 7753–7762.

Pérez, L., Rodríguez-Jiménez, S., Rodríguez, N., Usamentiaga, R., García, D. F., & Wang, L. (2020). Symbiotic human–robot collaborative approach for increased productivity and enhanced safety in the aerospace manufacturing industry. *The International Journal of Advanced Manufacturing Technology*, *106*(3-4), 851–863. https://doi.org/10.1007/s00170-019-04638-6

Peternel, L., Kim, W., Babič, J., & Ajoudani, A. (2017). Towards ergonomic control of human-robot co-manipulation and handover. 2017 IEEE-RAS 17th International Conference on Humanoid Robotics (Humanoids), Birgmingham, UK, 15 – 17 November 2017, pp. 55–60.

Peternel, L., Tsagarakis, N., Caldwell, D., & Ajoudani, A. (2018). Robot adaptation to human physical fatigue in human–robot co-manipulation. *Autonomous Robots*, *42*(5), 1011–1021. https://doi.org/10.1007/s10514-017-9678-1

Qu, X., & Nussbaum, M. A. (2008). Simulating human lifting motions using fuzzy-logic control. *IEEE Transactions On Systems, Man, And Cybernetics-Part A: Systems And Humans*, *39*(1), 109–118. https://doi.org/10.1109/TSMCA.2008.2007996.

Realyvásquez-Vargas, A., Cecilia Arredondo-Soto, K., Luis García-Alcaraz, J., Yail Márquez-Lobato, B., & Cruz-García, J. (2019). Introduction and configuration of a collaborative robot in an assembly task as a means to decrease occupational risks and increase efficiency in a manufacturing company. *Robotics and Computer-Integrated Manufacturing*, *57*, 315–328. https://doi.org/10.1016/j.rcim.2018.12.015.

Roveda, L., Maskani, J., Franceschi, P., Abdi, A., Braghin, F., Molinari Tosatti, L., & Pedrocchi, N. (2020). Model-based reinforcement learning variable impedance control for human-robot collaboration. *Journal of Intelligent & Robotic Systems*, *100*(2), 417–433. https://doi.org/10.1007/s10846-020-01183-3

Sanchez-Lite, A., Garcia, M., Domingo, R., & Angel Sebastian, M. (2013). Novel ergonomic postural assessment method (NERPA) using product-process computer aided engineering for ergonomic workplace design. *PloS One*, *8*(8), Article e72703. https://doi.org/10.1371/journal.pone.0072703

Snoek, J., Larochelle, H., & Adams, R. P. (2012). Practical bayesian optimization of machine learning algorithms. *Advances in Neural Information Processing Systems*, *25*.

Snook, S. H., & Ciriello, V. M. (1991). The design of manual handling tasks: revised tables of maximum acceptable weights and forces. *Ergonomics*, *34*(9), 1197–1213. https://doi.org/10.1080/00140139108964855

Stack, T., Ostrom, L. T., & Wilhelmsen, C. A. (2016). *Occupational ergonomics: A practical approach*. John Wiley & Sons.

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT press.

U.S. Bureau of Labor Statistics (2020, May). *Occupational injuries and illnesses resulting in musculoskeletal disorders (MSDs)*.

van der Spaa, L., Gienger, M., Bates, T., & Kober, J. (2020). Predicting and optimizing ergonomics in physical human-robot cooperation tasks. 2020 IEEE International Conference on Robotics and Automation (ICRA), 31 May 2020– 31 August 2020, pp. 1799–1805.

Vysocky, A., & Novak, P. (2016). Human-Robot collaboration in industry. *MM Science Journal*, *2016*(02), 903–906. https://doi.org/10.17973/mmsj.2016_06_201611

Yang, L., & Shami, A. (2020). On hyperparameter optimization of machine learning algorithms: Theory and practice. *Neurocomputing*, *415*, 295–316. https://doi.org/10.1016/j.neucom.2020.07.061.

Yazdani, A., Novin, R. S., Merryweather, A., & Hermans, T. (2021). Ergonomically intelligent physical human-robot interaction: Postural estimation, assessment, and optimization. *ArXiv Preprint ArXiv:2108.05971*.

Yazdanirad, S., Khoshakhlagh, A. H., Habibi, E., Zare, A., Zeinodini, M., & Dehghani, F. (2018). Comparing the effectiveness of three ergonomic risk assessment methods—RULA, LUBA, and NERPA—to predict the upper extremity musculoskeletal disorders. *Indian Journal of Occupational and Environmental Medicine*, *22*(1), 17–21. https://doi.org/10.4103/ijoem.IJOEM_23_18

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