Mitigating the risk of musculoskeletal disorders during human robot collaboration: a reinforcement learning approach

Ziyang Xie[a], Lu Lu[a], Hanwen Wang[a], Bingyi Su[a], Yunan Liu[a], Xu Xu[a]
[a]Edward P. Fitts Department of Industrial and Systems Engineering
North Carolina State University

Work-related musculoskeletal disorders (MSDs) are often observed in human-robot collaboration (HRC), a common work configuration in modern factories. In this study, we aim to reduce the risk of MSDs in HRC scenarios by developing a novel model-free reinforcement learning (RL) method to improve workers' postures. Our approach follows two steps: first, we adopt a 3D human skeleton reconstruction method to calculate workers' Rapid Upper Limb Assessment (RULA) scores; next, we devise an online gradient-based RL algorithm to dynamically improve the RULA score. Compared with previous model-based studies, the key appeals of the proposed RL algorithm are two-fold: (i) the model-free structure allows it to "learn" the optimal worker postures without need any specific biomechanical models of tasks or workers, and (ii) the data-driven nature makes it accustomed to arbitrary users by providing personalized work configurations. Results of our experiments confirm that the proposed method can significantly improve the workers' postures.

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INTRODUCTION

Musculoskeletal disorders (MSDs) are the most common occupational injuries in the industry (Kang et al., 2014; Stack et al., 2016). The causes of MSDs can be repetitive motions, awkward postures, and high workloads (Stack et al., 2016). There were approximately 273,000 day-away-from-work cases related to MSDs reported in 2017 in the U.S. (U.S. Bureau of Labor Statistics, 2020). The adoption of industry robots can relieve workers from repetitive work and heavy workloads (Gualtieri et al., 2021). For example, a variety of robots have been designed to move heavy parts for human workers, and consequently can help reduce the risk of low-back MSDs. Nevertheless, not all tasks can be completed by robots alone. Some still require human workers working together with robots for quality control purposes, especially in advanced manufacturing and assembly (Bi et al., 2021). This human-assisted work configuration is called human-robot collaboration (HRC).

Yet the risk of MSDs may still exist in HRC tasks. When robots are pre-programmed to work at a preset position, this position may not be suitable for all workers due to their individual variability such as body dimensions (Figure 1), preferences, and other personalized characteristics. Consequently, HRC without personal customization may lead to awkward postures for workers and in turn, increase MSDs risks(Anita et al., 2014).

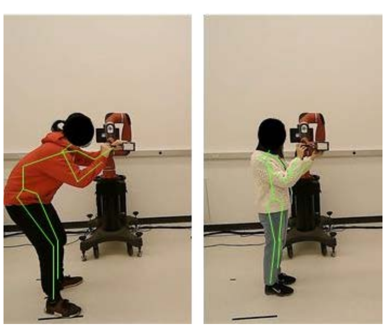

Figure 1. A set position may not be suitable for workers with different body features. A taller worker (left) has to bend down to finish an HRC tasks

To reduce the risk of MSDs during HRC, the robot-end effector position should be adaptive and take into consideration ergonomics factors. To date, a number of optimization methods have been proposed to improve workers' posture during HRC by adjusting the location of robots' end effectors. In some studies (Kim et al., 2017; Peternel et al., 2018), optimization methods are developed based on body joint loadings that are estimated through a biomechanical model or measured from EMG feedback. Yet, the estimated joint loading can be sensitive to the validity of the adopted biomechanical models. In some other studies (Busch et al., 2017, 2018; Roveda et al., 2020), optimizations are performed on ergonomic assessment indicators. For example, in a recent study (Liau & Ryu, 2020), a Rapid Upper Limb Assessment (RULA) score is used as an indicator of workers' posture health during HRC. RULA is a widely used and validated ergonomics tool in evaluating the overall MSD risks (McAtamney & Corlett, 1993; Micheletti Cremasco et al., 2019) A greater RULA score indicates a greater risk of MSD.

Traditionally, assessment and calculation of RLUA score require safety practitioners to manually code body postures. This process is time-consuming and requires ergonomic expertise. In previous studies, researchers have adopted wearable inertial measurement units to track workers' body postures and estimate the ergonomic score for optimizing a robot's end effector location and improving workers' posture (Busch et al., 2017, 2018). Nevertheless, wearable sensors may be not suitable in certain field applications because they can affect worker's natural body motion at work. An alternative way to track body motion and automatically assess the RULA score is through camera and computer vision (Li et al., 2020)

Once workers' ergonomics assessment scores are computed, one can further apply different optimization algorithms to adjust robots' end effector locations with an objective of minimizing workers' ergonomic assessment risk. Prior studies have proposed optimization methods where the ergonomic assessment was performed on the simulated human pose during HRC tasks (Busch et al., 2017; Yazdani et al., 2021). However, human pose simulation can be an ill-posed problem (Qu & Nussbaum, 2008) because 1) workers have 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). To address these issues, a novel model-free reinforcement-learning (RL) algorithm is proposed in this study, which is a trial-and-error method (Sutton & Barto, 2018) that can optimize workers' RULA scores without needing a full body biomechanical model. Prior to this study, RL methods have been applied in robot action planning in different scenarios (Degris et al., 2012; Hu et al., 2019) and these applications exhibit promising potentials in optimization tasks.

In the current study, we developed a novel model-free RL method called Gradient-based Online Learning Algorithm in HRC (GOLA-HRC) which can be used to effectively minimize workers' RULA scores. The data-driven nature of the proposed method allows the robot to "learn" the optimal effector location and provide personalized configurations for individual worker. We further conducted a preliminary experiment to examine the effect this algorithm on worker posture improvement. Results of our experiments confirm that our approach is effective in improving the worker's posture.

METHOD

Automatic RULA score estimation

Human pose reconstruction Adopting a computer vision method developed in our previous study (Wang et al., 2021), the present work will calculate the RULA score from workers visualized joint angles. The first step in RULA score estimation is to reconstruct workers' poses from a single RGB camera. The VideoPose3D model is adopted which predicts the 3D human key-joint positions of a worker from camera captured videos. The mean absolute error of the estimated joint positions is reported to be less than 50 mm (Pavllo et al., 2019).

A refined RULA score. Traditional RULA assessment is a step function which intends to be insensitive when the change of body joint angle is relatively small (Note that the gradient of the RULA is zero). To establish a refined RULA score so that it can be used to calculate the gradient during optimization, we propose to fit the RULA score into a continuous linear function (Figure 2), which is referred as continuous RULA (cRULA). Because RULA does not consider the lower extremity posture, we added 'knee' into cRULA in order to capture deep squat postures. Specifically, a punishment score of 2 is added to cRULA whenever the workers' knee angles were over 20 degrees. The scores of all joints will be then summed up to form an overall cRULA score that will be used in our RL algorithm.

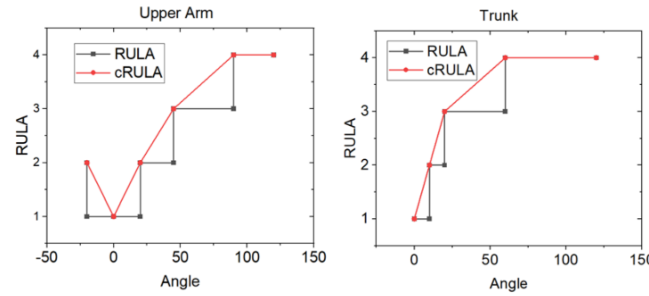

Figure 2. Comparison of RULA and cRULA score of worker's upper arm. Left: Upper arm cRULA vs RULA; Right: Trunk cRULA vs RULA

Gradient-based online learning in HRC (GOLA-HRC)

Variables to adjust An HRC task was designed as a testbed for developing the GOLA-HRC method. In this task, the participants were asked to insert wires into a specific location on a breadboard gripped by a collaborative robot (Sawyer, Rethink Robotics). This task simulated a common human-assisted assembly task. Workers' posture is determined by the location and orientation of the robot's end-effector. Specifically, the adopted robot's end-effector has 6 degree of freedom (DoF), including three translational DoF (x, y, z, shown in Figure 3) and three rotational DoF (α, β, γ, Figure 3). Therefore, one can adjust these six variables to change workers' RULA score. To reduce the state space and improve learning speed, in this study some variables that did not substantially affect workers' pose were excluded. For instance, the participants were free to move during the experiment. Therefore, the end effector's horizontal translational motions (x and z, Figure 3) would not affect workers' postures and thus could be excluded. Similarly, the rotational motion along the β-axis (Figure 3) could be compensated by the horizontal motions of workers. In addition, due to the nature of the adopted fine wire insertion task, the rotational motion along the γ-axis does not affect workers' posture. Therefore, there were two essential variables to adjust during the RL: translational motion along the y-axis, which determined the height of the end-effector, and rotational motion along the x-axis, which determined the pitch angle of the end-effector.

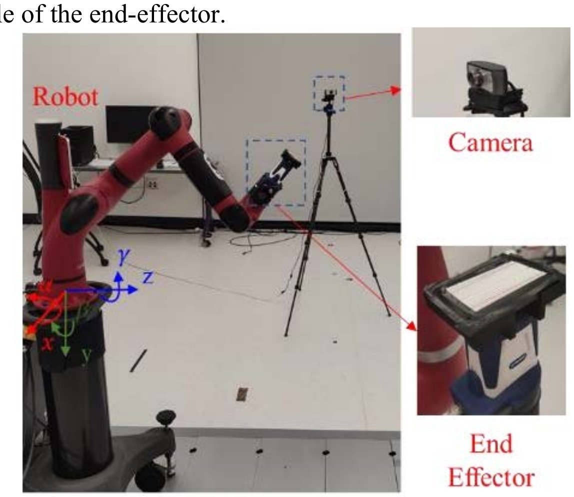

Figure 3. Experimental setting: A camera is placed 3 meters away from the robot. The origin of the robot coordinates is set

on the robot base. The directions of translational axes x, y, z and rotational axes α, β, γ are marked on the figure.

RL algorithm. The algorithm searches for a set of variables that minimize the cRULA score of a worker. Following the estimation method described earlier, a cRULA score is to be estimated each time a worker finishes a fine wire insertion task, and a posture-cRULA pair is generated.

The gradient ∇_{t_p} and ∇_{t_o} are defined in Equation (1) and (2). This gradient indicates how the cRULA is improved or deteriorated by translational motion h and rotational motion a. Using the gradient, the future end effector location at step t + 1 is determined by the previous end effector location at time t and search step lengths (h and a) as described in Equation (3). Inspired by the optimizer Adams (Sun et al., 2019), we introduce a discounting factor α to control the learning rate dynamically. We also impose constraints on the step lengths s_p and s_o to guarantee a stable search process. Learning rates l_o and l_p involve after each iteration according to Equation (4). The termination condition is defined in constraint (5). Here, $\epsilon > 0.3$ is an error parameter that trades off between convergence speed and solution precision. Note that when ϵ is large (small) the algorithm converges more quickly (slowly) but yielding a more (less) accurate solution. The flow chart of experiment process description was shown in Figure 4, and the detailed algorithm is shown in Algorithm 1.

$$\nabla_{t_p} = (RULA_t^p - RULA_t)\ /\ h, \tag{1}$$

$$\nabla_{t_o} = (RULA_t^o - RULA_t)\ /\ a \tag{2}$$

$$h = \min\left(l_p \cdot \nabla_{t_p},\ s_p\right) \cdot \frac{\nabla_{tp}}{|\nabla_{tp}|},\ a = \min(l_o \cdot \nabla_t,\ s_o) \cdot \frac{\nabla_{to}}{|\nabla_{to}|} \tag{3}$$

$$P_{t+1} = P_t + h\ O_{t+1} = O_t + a,\quad l_p, l_o = \alpha \cdot l_p, \alpha \cdot l_o \tag{4}$$

$$|\nabla_{t_p}| < \epsilon,\ |\nabla_{t_o}| < \epsilon \tag{5}$$

Here ∇_t is the gradient, P_{t+1}, P_t are positions at step t + 1 and step t. l_p and l_o are the learning rates of the position and the orientation, s_p and s_o are step length constraints of the position and the orientation. α is the discounting factor. $\epsilon > 0$ is the error parameter one may select in order to achieve a proper tradeoff between convergence speed and solution precision for GOLA-HRC; in particular, when ϵ is large (small) the algorithm converges more quickly (slowly) but yielding a more (less) accurate solution..

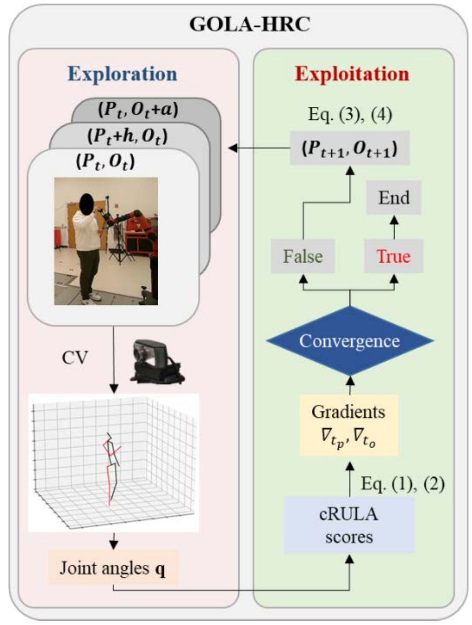

Figure 4. Flow chart of GOLA-HRC.

Algorithm 1: 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 $P_t = P_{t-1} + h_{t-1}, O_t = O_{t-1} + a_t$

Move to (P_t, O_t), Record $RULA_t$;

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

Move to $(P_t, O_t + a_t)$, record $RULA_2^o$;

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

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

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

end loop

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

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

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

The initial end effector location in y axis and orientation α are set to 1.055m and 0 degree (along x axis of the robot). This setting will place the breadboard at the 50%ile elbow height over the entire population as elbow height is referred as a preferred height for assembly tasks in terms of reducing MSD risks (Freivalds & Niebel, 2008).

Participants, collaboration task and experiment setup

To evaluate the effectiveness of the GOLA-HRC method, we performed a validation study. As shown in Figure 3, a gripper was 3D printed and attached to the end effector of the collaborative robot to hold a breadboard (5.5 cm x 17 cm). The robot was connected to a workstation with a GPU (NVIDIA RTX 2080Ti) that supported computer vision algorithms. All the computer vision algorithms, cRULA score calculations, and RL algorithm were programmed in Python (Ver. 3.6) on Linux platform (Ver. 16.04). The workstation-robot communication was through Intera SDK (Ver. 5.3), which is based on Robot Operating Systems (ROS Kinetic). A webcam (Model: MF920P, Spedal) was placed 3 meters away from the robot to capture the image of the participants and was connected to the workstation.

Eight participants were recruited (4 males and 4 females, average age of 26.3 ± 2.1, height of 173 ± 12.0 cm, weight of 73 ± 16.3 kg). During the experiment, each participant was first asked to repetitively perform the wire insertion task until the estimated cRULA scores through computer vision converged with $\epsilon = 0.3$, that is, until $|\nabla_{t_p}| < 0.3$ and $|\nabla_{t_o}| < 0.3$. After each repetition, the location of the robot's end effector was adjusted by applying the GOLA-HRC for minimizing the cRULA score. The end effector location with the converged cRULA score is referred as "*learnt location*" hereafter. The participants were then asked to move the end-effector to positions that they felt most comfortable to work with. This position is referred as "*worker-selected location*" hereafter. Once the *learnt location* and *worker-selected location* were determined, the participants performed the wire insertion task three times under each location as well as the initial end effector location (50%ile elbow height). The sequences for each participant of the testing were counter-balanced.

Statistical analysis

The cRULA score associated with the *learnt location* was compared with those associated with the elbow height and *worker-selected* locations. Analysis of variance (ANOVA) and post-hoc Tukey test were performed to investigate whether the different end-effect locations had significant effects on cRULA.

RESULTS

As expected, the ANOVA indicated that the end-effector locations had significant effects on the workers' cRULA score ($F(2, 14) = 34.05$, $p < 0.0001$).The result of the post-hoc Tukey test indicates that the cRULA score of *learnt location* and *elbow height* were significantly different ($p = 0.0026$), and the cRULA score of *worker-selected* and *elbow locations* were significantly different ($p = 0.0074$). Figure 5 shows the means and quantiles of the result.

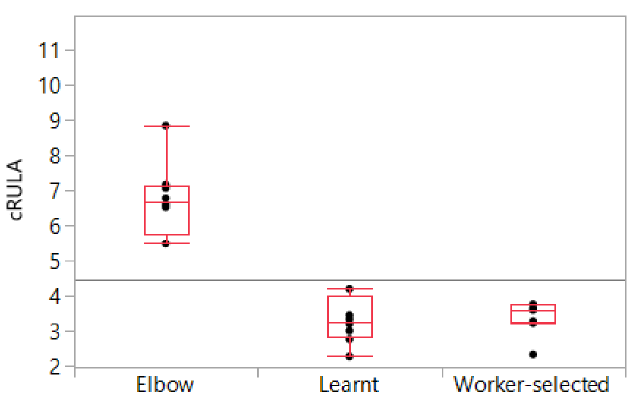

Figure 5. Means and quantiles of cRULA score under different end effector location. The red box plots show the 90%, 75%, 50%, 25%, 10% quantiles.

DISCUSSIONS

cRULA score vs Iterations

Figure 6 shows how the GOLA-HRC improved a participant's working posture step by step. For this specific participant, the initial position was too low and resulted in a forward trunk bending posture. By calculating the gradient of the cRULA score, the algorithm adjusted the location and orientation of the end-effector until the cRULA score converged.

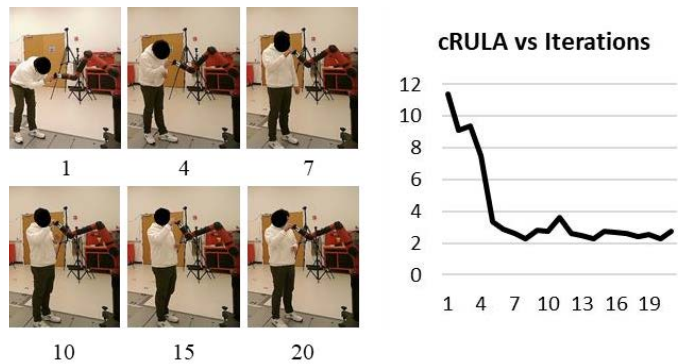

Figure 6. Left: Six postures over 20 iterations. The numbers below indicates the number of iterations. Right: The cRULA scores over each iteration.

Effectiveness of GOLA-HRC .

As expected, the cRULA scores of the *elbow height* were the greatest on average and significantly different from the cRULA scores of the *learnt locations*, which indicates that the GOLA-HRC can effectively improve the posture of a worker and thus reduce the MSD risks. In addition, the cRULA scores of *worker-selected location* were significantly lower than the cRULA scores of *elbow height*. This is aligned with the assumption in psychophysics studies – workers to some extent are aware of whether a specific body posture is safe or not for them (Snook & Ciriello, 1991).

Personalization of cRULA

Another appeal of the proposed model-free RL method is that the optimization criteria can be conveniently personalized for workers. For instance, workers who already have neck discomfort should ensure their neck is in a neutral posture. In that case, one can apply a weight factor to the Neck score in cRULA before applying the RL algorithm. In a preliminary experiment, the robot's end effector moved to a higher position when the weight factor of Neck is set to two and thus resulted in a smaller neck forward bending angle but a greater arm elevation angle (Figure 7)

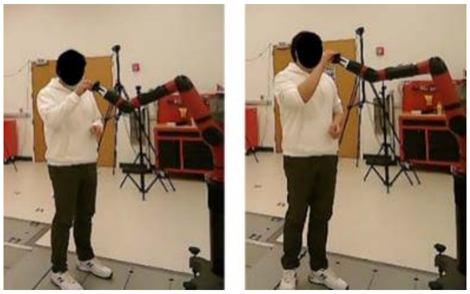

Figure 7. Left: The optimized posture in original RULA. Right: The optimized posture with doubled weight on neck angle.

Limitations

A few limitations need to be addressed. First, as this study adopted the computer vision algorithm, a camera needs to be placed where its field of view is not blocked. Otherwise the error of identified joint location will be significantly greater. To address this problem, one could consider using a multi-camera computer vision system. Second, assessment of RULA scores is based on workers' joint angles as well as workloads (e.g., the weight of the material being handled). As this study focuses on improving the workers' postures, the workload factors were not included in the assessment.

CONCLUSION

In this study we proposed a worker posture optimization method during HRC. A computer vision method was first adopted to recognize human posture and estimated a cRULA score. A model-free gradient descent optimization algorithm was then developed to lower the cRULA score of a worker. The preliminary experimental result indicated that the GOLA-HRC had a good potential to effectively lower workers' cRULA score during HRC tasks and thus reduce the risk of MSDs. Next, we will recruit additional participants to validate the generalizability of GOLA-HRC.

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