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Improving Postural Ergonomics during Human–Robot Collaboration Using Particle Swarm Optimization: A Study in Virtual Environment

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Abstract: Musculoskeletal disorders caused by poor work posture are a serious concern in the industry since they lead to absenteeism and medical leave from work. In the context of human–robot collaboration, this issue can be mitigated if collaborative robots support human workers to perform their tasks more ergonomically. In this work, we propose a method to optimize human posture during human–robot collaboration using the Particle Swarm Optimization (PSO) algorithm. Our approach involves assigning an appropriate location to the robot's end-effector to minimize the distance between the optimized posture of the human and their current posture in the working space. To measure human posture, we use the Rapid Entire Body Assessment score (REBA) calculated from body joint angles captured by a Kinect camera. To validate the effectiveness of our proposed method, we conducted a user study with 20 participants in a virtual reality environment. The PSO algorithm could position the robot end-effector to the optimal position close to real time. Our results showed that our method could improve ergonomics by 66%, indicating its potential for use in human–robot collaborative applications.

Keywords: human–robot collaboration; optimization; ergonomics; PSO algorithm

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1. Introduction

In industrial environments, workers suffer from high physical and cognitive pressure and this might result in irreparable health problems [1–3]. Some of those are musculoskeletal disorders (MSDs), which are related to physical pressure [4,5]. This affects about 40 million workers in Europe and is the main reason for workers' leave requests and injuries, costing up to EUR 240 billion annually to companies and governments [6–8]. Specifically, a survey in 2015 showed that 59.31% of workers in Europe reported suffering from at least one of three forms of MSD (backache, neck pain, shoulder pain and pain in the upper limbs, and pain in the lower limbs) [9]. In the global context, work-related musculoskeletal disorders account for 40% of worldwide compensation expenses of occupational and work-related accidents and illnesses, and lower back pain is the major cause of years lived with disability [10,11]. To address these issues, using collaborative robots (or cobots) to share the workload with the workers is a potential solution. The working condition is consequently improved and the risk of injuries is reduced [12].

When a worker collaborates with a robot, the physical pressure can be reduced at two levels. At the task level, a task allocation method can be used to effectively hand off sub-tasks to the robot and the worker based on their capabilities [13–15]. At the sub-task level, the physical workload can be further reduced by optimizing the robot's end-effector position during the collaborative task. This allows the worker to perform the task more ergonomically.

Several approaches have been proposed to decrease the workload of workers to improve ergonomics and avoid MSDs. One approach is to improve the workspace design. Das and Sengupta proposed a guideline to establish an ergonomic workstation layout based on the anthropometry of the user population [16]. Michalos et al. used immersive virtual reality to examine and improve the industrial workplace [17]. Feyen et al. proposed a PC-based program that considers the biomechanical risk of accidents in a setting of automobile assembly in the design of the workplace [18]. Mateus et al. proposed a systematic design method for human–robot shared workstations [19]. The workstation's architecture is established by examining the CAD model, product, and assembly sequence limitations to determine the ergonomics of the assembly duties. Another strategy is to improve posture while doing a task. Merikh et al. introduced a generic method that, depending on job restrictions, finds the worker's ideal ergonomic position in real time. In [20], the algorithm offers an ideal postural position for performing activities in an industrial setting to reduce the risk of work-related MSDs. Zhang et al. established a unified approach to assess the productivity and ergonomic performance of both manual operations and collaborative robot assembly systems [21]. Colim et al. provided a paradigm to support the safe design and conception of ergonomically driven collaborative robotics workstations [22]. Their methodology consists of four primary steps: (i) the characterization of the starting state, (ii) the risk assessment, (iii) the development of criteria for a secure design, and (iv) the conception of the hybrid workstation. The framework's results indicate that the proposed technique provides a sufficient basis for accelerating the design and development of new human-centered collaborative robotic workstations.

Methods for assessing the human body's posture are crucial for evaluating and enhancing ergonomics. Observational approaches are well-known ergonomic instruments that serve a variety of applications [23]. Examining the operator's body postures and manually encoding the expected joint angles from a video clip of the job are systematic operations. Yet, because of their paper-based nature, they are imprecise and time-consuming [24]. Time-of-flight cameras and other vision-based person-tracking technologies allow automated posture assessment. They provide an inexpensive technique to evaluate the ergonomics of the operator on the work floor. In addition to human kinematics sensing, a variety of models have been developed to measure the body's dynamics [25–27]. Due to their intricacy, however, such models are usually impossible to construct online and may only be used offline.

In this work, we propose a novel framework for postural optimization that improves worker comfort. In this framework, we attempt to find the optimal location for the robot's end-effector by the Particle Swarm Optimization (PSO) algorithm to reduce the ergonomics to the most optimal value [28]. The PSO algorithm is a better fit for our work as compared to other intelligent algorithms because of its simplicity, high execution efficiency, and ability to handle nonlinear problems. Additionally, it avoids the need for complicated mathematical formula derivations and parameter selection [29]. The ergonomic value is measured by the REBA (Rapid Entire Body Assessment) score system because it provides a quantitative, rapid, and brief explanation of a posture's overall ergonomic status [30]. There is no restriction in using the calculation method of ergonomics during human–robot collaboration, and according to the needs of the research, other measurement methods such as RULA (Rapid Upper Limb Assessment) or OWAS can be used. While there are various methods available for evaluating the risk of musculoskeletal disorders, the REBA method was chosen since it can give a quantitative measure for the ergonomic state of the worker's posture. Another reason for choosing REBA is because we want a full body posture assessment. Since the value of the REBA score in the lower limb was always equal to 1 and the users in this study were always in a standing position while working with the robot, we omitted the calculation of the lower limb. We conducted a user study with 20 participants to validate the proposed method in an assembly task, which is the most widely used type of task in human–robot collaboration in the industry. The collaborative task was set up in a virtual reality environment (VR) since it allows developers to quickly establish and test the many interactive scenarios before actually building them. Another advantage is safety due to the lack of physical risks associated with interacting with real robots, especially at the early stages of system development. Other advantages are low cost and no robot maintenance costs [31–33]. Additionally, the virtual environment provides a close-to-reality simulated environment to study task performance in work environments and workers' ergonomics [34,35].

The rest of the paper is organized as follows. The problem statement is formulated in Section 2. The methodology is described in Section 3. The implementation is detailed in Section 4, including the human–robot collaborative task, hardware, and software. The user study to validate the proposed method is presented in Section 5. The discussion and conclusion are given in Sections 6 and 7.

2. Problem Statement

In the course of human–robot collaboration, some positions of the human body may be non-ergonomic and may result in injury to the human operator. For example, in the workplace, a worker tries to lean forward multiple times to pick up an object for assembling a workpiece, which puts more pressure on his/her backbone. In this context, the robot can assist the human by appropriately positioning for the end-effector such that the ergonomics are enhanced during the task. The new location for the robot's end-effector should be calculated and assigned to the robot regarding the user's ergonomics if an improper posture is detected. For this purpose, a mathematical method needs to be developed to determine the optimal location for the robot's end-effector that leads to an ergonomically optimal posture for the human.

3. Methodology

In this section, we present the framework of our novel method that optimizes the robot's end-effector position based on the worker's posture to improve ergonomics. As indicated in Figure 1, the ergonomics framework is composed of three parts. First, a 3D skeleton tracker calculates and sends the joint angles of the human body for visualization. Second, these data are used to generate the current REBA ergonomic score. The current REBA score and the optimum position REBA score are sent to the user's PSO-based ergonomic optimization system in order to reduce the disparity between the current position and the optimal position. Thirdly, the optimizer transmits the optimum position to the workpiece position controller, which modifies the robot's behavior to place the user in a more advantageous position for co-manipulation/handover operations.

3.1. Rapid Entire Body Assessment (REBA)

In this work, we use Rapid Entire Body Assessment (REBA) methods that assess postures during static or rapidly changing actions. The values are incorporated into a final evaluation of the given posture and range from 1 to 15 (from comfortable position to unacceptable ergonomic position, calling for immediate action). Researchers provide a brief explanation of the ergonomic status of the user in [36], alongside the posture joints' position and orientation in real time, which are captured from the skeleton tracking system.

The REBA score system gives a quantitative, fast, and brief explanation of posture's overall ergonomic status. By incorporating the skeleton tracking system, we are able to continuously monitor the ergonomic posture of workers. This means these data are updated whenever their posture changes and are used to evaluate ergonomics.

In the REBA calculation method, the human skeleton is divided into two groups. The first group includes the neck, trunk, and legs. The second group includes the arm, lower arm, and wrist. A value is defined based on its angle in its idle position for every part in each group. For the robot's end-effector, the final REBA score of the user can be used as a measure for starting the optimization algorithm. In this work, we intend to investigate the improvement of ergonomics with optimized robot end-effector locations with the PSO algorithm.

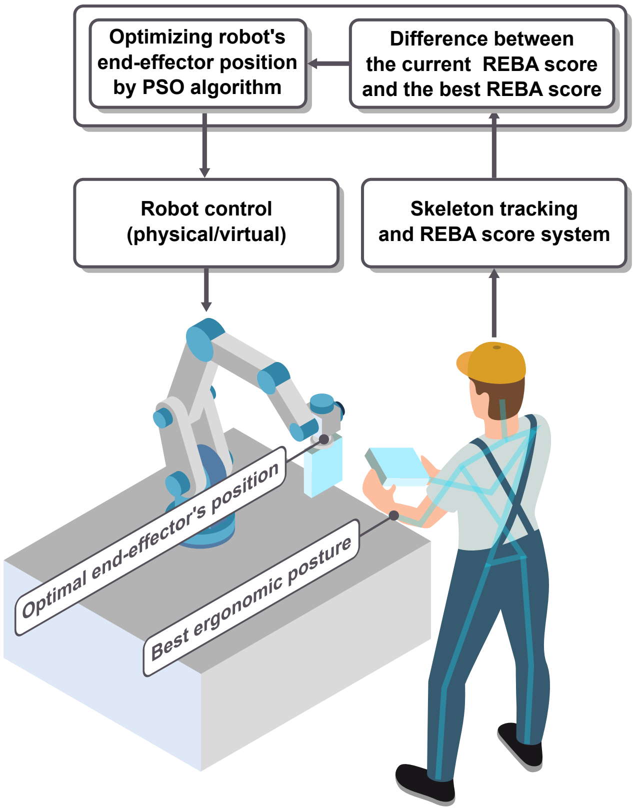


Figure 1. The ergonomics controller scheme. The human skeleton is tracked to calculate REBA scores. The robot's end-effector position is optimized by the PSO algorithm and executed on the robot platform.

3.2. Particle Swarm Optimization (PSO)

The Particle Swarm Optimization (PSO) algorithm was presented by Kennedy and Eberhart [28]. They originally intended to use existing social models and social relationships to create a type of computational intelligence that did not require individual special abilities. Their work led to the creation of a powerful optimization algorithm, called the Particle Swarm Optimization Algorithm (PSO). This method is adapted from the collective performance of groups of animals such as birds and fish. There are a number of creatures in the PSO, which we call particles, and they are scattered throughout the search space. Each particle calculates the value of the objective function at the position in the space in which it is located. The crowd chooses a direction to move. After performing the mass move, one step of the algorithm ends. These steps are repeated several times until the desired answer is obtained.

The objective function for our method is

$$min \;\; J(k) = \frac{1}{2}\int_0^t \left[(r-y)^T \, Q(r-y) + u^T R u \right] dt \tag{1}$$

$$u = r - kx \tag{2}$$

$$Q \geq 0 \text{ and } R > 0$$

In this study, we propose the formula as a performance index (J) that is designed to minimize ergonomics-related issues. The formula incorporates the REBA score evaluation system, which is widely used to evaluate the ergonomic risks associated with different postures and movements.

In the formula, r represents the most optimal ergonomic posture for the human, as determined by the REBA score evaluation system, with a numerical value of "1". The output of the REBA system for the human's current ergonomic posture is denoted as y. The goal of the formula is to minimize the difference between the most optimal posture (r) and the current posture (y), as reducing this difference can potentially improve ergonomics and reduce the risk of musculoskeletal disorders.

The input to the formula is denoted as u, which is defined as $[r - kx]$, where x represents all possible states of the system, i.e., the locations of the robot's end-effector. The term kx represents the effect of the optimization algorithm, where k is a factor with three decimal places that ranges between -1 and 1 and is set by the optimization algorithm. The purpose of this factor is to allow the system to adjust the robot's end-effector location (x) in order to decrease the difference between the best REBA score ($r = 1$) and the worker's current ergonomics (y). By adjusting the end-effector location, the ergonomics of the user during handover can be changed, potentially improving the overall ergonomics of the task.

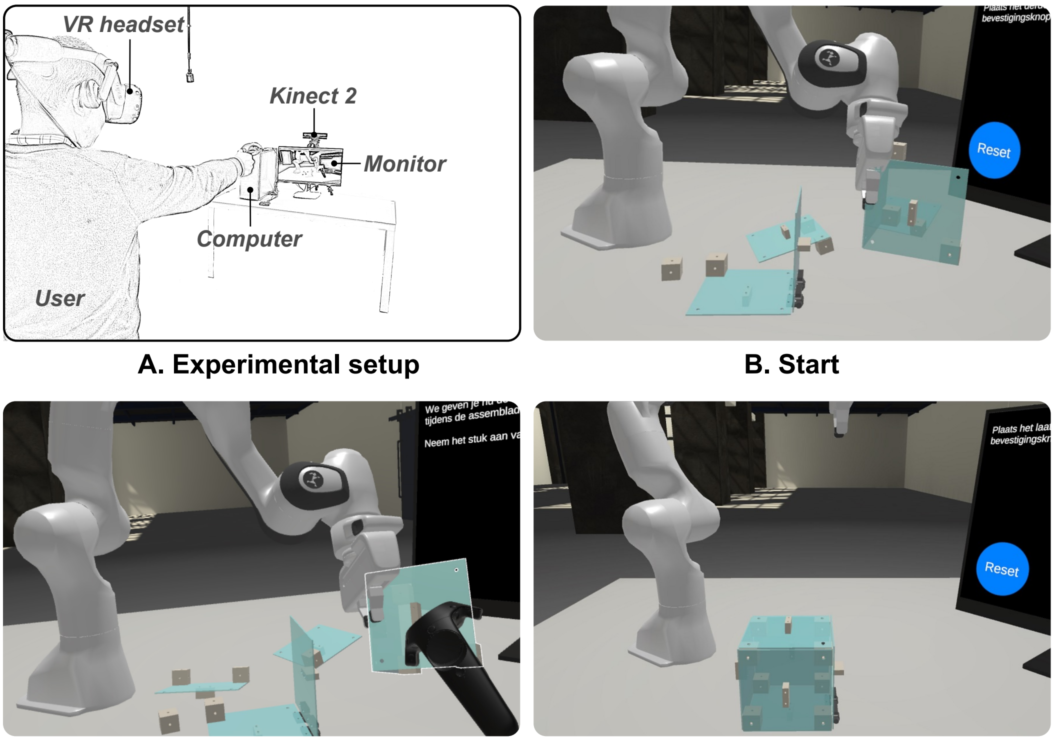
To optimize the robot's end-effector motions, we utilized the Particle Swarm Optimization (PSO) algorithm, which is a popular optimization algorithm known for its speed and accuracy. The values of Q and R in the formula were determined through manual experimentation, considering criteria such as convergence speed and minimization of the REBA score. Since in this manual experimentation we investigated different values for Q and R, other values lead to suboptimal output for the proposed method. It was observed that changing the values of Q or R resulted in the PSO algorithm converging to an end-effector position that was associated with a suboptimal REBA score, highlighting the importance of choosing appropriate values for these parameters [37]. The proposed formula has the potential to enhance human ergonomics during human–robot interaction tasks by minimizing the difference between the most optimal posture and the current posture of the worker. The problem is to minimize the above equation to avoid non-ergonomic postures that we applied ODE45 in MATLAB to solve this problem [38].

3.3. Finding the Optimal Location for the Robot's End-Effector

By determining the appropriate location to place the end-effector of the robot in front of the user, the PSO algorithm helps the human to bear less pressure when interacting with the robot and the system. According to Equation (1), the PSO algorithm tries to find the optimal location for the robot by finding the appropriate value for k. During the process of finding the best placement of the robot's end-effector, we examine the space in front of the human. In order to reduce the processing load and increase the performance speed of the method in determining the appropriate location for the robot's end-effector, we calculated two of the three dimensions of the workspace, the height of the human elbow from the ground and the distance between the robot and the human via the skeleton tracking system. This is according to the definition of REBA and according to appropriate ergonomics. Based on this processing, the obtained point is used to determine the most suitable location for the robot's end-effector within the virtual environment. Using the current REBA score of the user as feedback and determining the amount of difference achieved in the review stage, we attempt to have the robot make the least movement possible while the workpiece passes to the human. After the appropriate point for the robot's end-effector is sent to the robot control (either physical or virtual), the robot uses that point to position its end-effector to improve user ergonomics. The updated ergonomic value is also analyzed.

4. Implementation

In this section, we present details of the implementation of our proposed method. The human–robot collaborative environment was set up in VR due to its advantage of quickly and safely establishing and testing collaborative scenarios in a close-to-reality situation. The experimental setup is illustrated in Figure 2A. The workspace is modeled using the Unity3D game engine and with the ROS# package provided by Siemens [39,40]. In this environment, a human worker and a robot collaborate to assemble products designed using the ExperienceDNA tool [41]. An HTC Vive Pro was used to interact with a virtual reality environment. A Kinect 2 camera was used for skeleton tracking. The specifications of the system used to set up the simulated virtual reality environment, REBA score calculations, and the processes performed in this work are as follows: CPU: AMD Ryzen™ 9 5950X, 64 GB RAM; OS: Windows 10; GPU: Nvidia RTX 3070; HDD: Samsung SSD 970 1 TB. The virtual robot used during the collaborative task is Franka, a widely used robot platform in human–robot collaboration.



A. Experimental setup **B. Start**

C. In progress **D. Finish**

Figure 2. The system implementation. (**A**) The experimental setup. (**B**–**D**) The human–robot collaborative task in virtual reality.

A user wears the VR headset and starts the assembly task in which the user and the robots collaboratively assemble a product consisting of 22 workpieces. The assembly task scenario is as follows (see Figure 2B–D). At the start, the workpieces are placed on the table. The robot hands over the workpieces one by one to the user to assemble the product. The task is finished when all workpieces are assembled correctly. At each step during the collaboration, the PSO algorithm selects the robot's optimal end-effector positions for handovers. The evaluation involved measuring users' ergonomics from different starting points as feedback for the system to calculate the error between the previous handover and the most optimal location for handover. This error is influenced by factors such as height, handedness, and distance from the robot.

In most cases, the optimization process took less than 5 s to reach the settling point. Figure 3 shows the control effort and the output of an example case. The value of k is calculated by the PSO algorithm (see Equation (1)). In this case, the system took 2.5 s to find the optimal solution. This time is comparable with the previous studies in human–robot object handover [42,43]. It is worth mentioning that this time depends on the speed of the robot, which needs to be within the safety regulation and the specific task and can be decreased by increasing the speed of the robot.

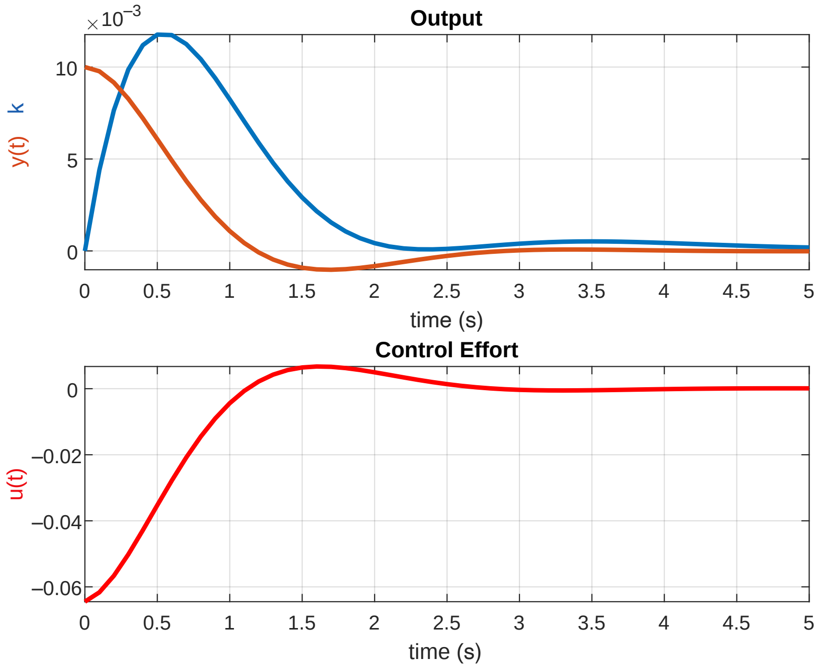


Figure 3. The output (orange) and the control effort (red) of the robot movement during the first 5 s in an example case. The value of *k* (blue) is calculated by the PSO algorithm. The system took around 2.5 s to settle.

5. User Study

The user study aims to investigate the effectiveness of applying the PSO algorithm in improving ergonomics during human–robot collaboration. The user study was conducted in a controlled environment with participants performing an assembly task together with a collaborative robot. By comparing the results to a baseline condition where no optimization was applied, we can demonstrate the advantages of using PSO for improving body ergonomics (see Figure 4).

5.1. Participants

For our study, we selected a diverse group of participants to investigate the potential to be applied to different users in the industry. In total, we recruited 20 participants (9 females, 11 males). Their ages ranged from 25 to 30 years. We also had both left-handed and right-handed participants (3 left-handed, 17 right-handed). Additionally, our participants had varying heights. These variations ensured the diversity of our participants, which contributes to the potential of applying our proposed method to diverse groups of users in real life.

5.2. Procedure

All participants received an explanation of the study and informed consent was obtained before participating in the study. Each participant was asked to perform an assembly task consisting of assembling workpieces in a VR environment in two conditions with a counter-balanced order. In the first condition (baseline), no optimization method was implemented and the robot's end-effector was always fixed. In the second condition, the PSO algorithm was used in guiding the robot's end-effector to the most optimal position. In both conditions, REBA scores were measured to assess the level of ergonomics in each condition. The calculated REBA scores were the total score, the trunk score, the upper arm score, and the lower arm score.

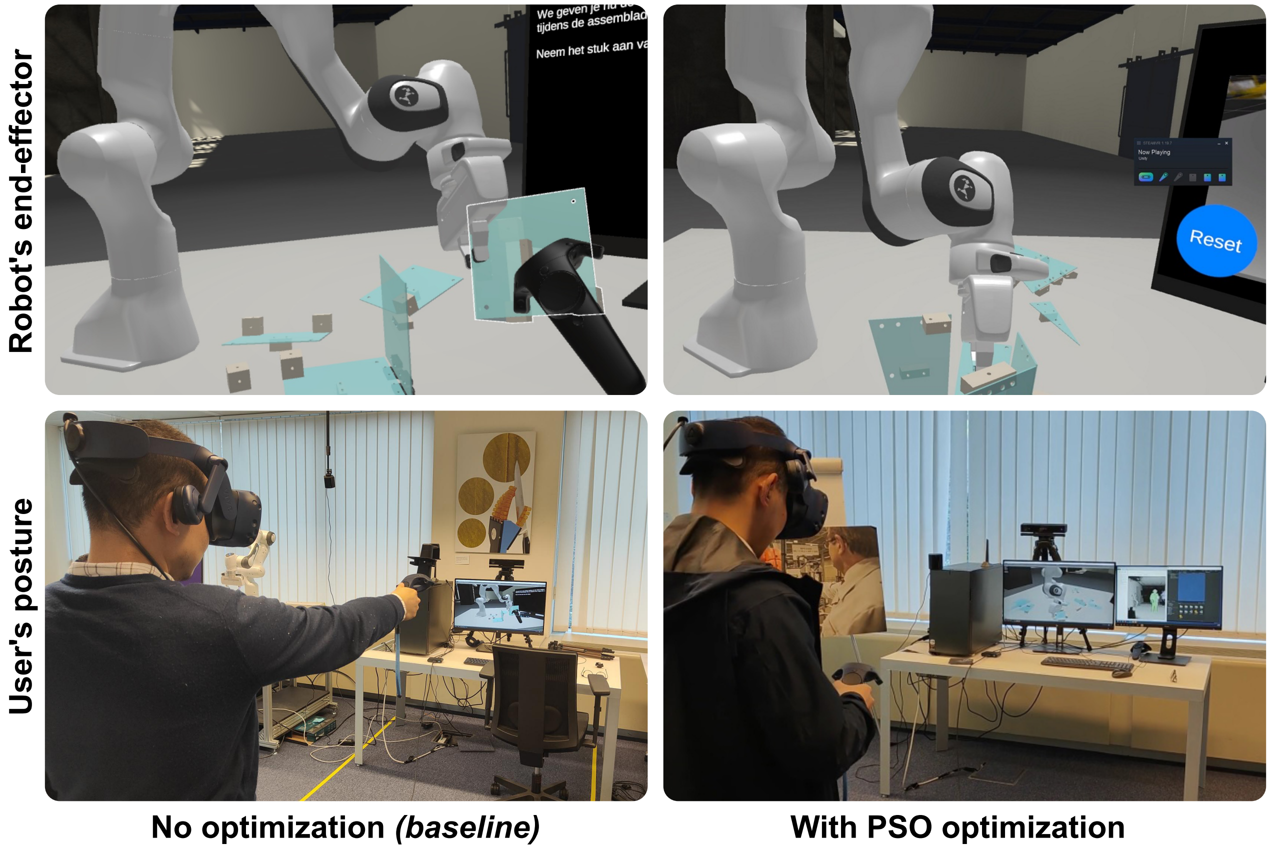


Figure 4. A user collaborates with a collaborative robot in a virtual reality environment. With PSO optimization of the robot's end-effector position, the user's ergonomics are improved compared to the baseline condition where no optimization was applied.

5.3. Data Analysis

Data were analyzed in Python using `pingouin` and `scipy` packages. Normality and homogeneity were checked by Shapiro–Wilk and Bartlett tests to determine the statistical tests. The significance level was set at 0.05.

5.4. Results

Results of four paired samples Wilcoxon tests showed that all REBA scores were improved in the PSO condition compared to the baseline (see Figure 5). The total REBA was significantly reduced from 3.55 $\pm$ 0.23 in the baseline to 1.19 $\pm$ 0.10 in the PSO condition ($p < 0.001$). The trunk score was significantly reduced from 3.83 $\pm$ 0.17 in the baseline to 1.08 $\pm$ 0.08 in the PSO condition ($p < 0.001$). The upper arm score was significantly reduced from 3.06 $\pm$ 0.17 in the baseline to 1.24 $\pm$ 0.08 in the PSO condition ($p < 0.001$). The lower arm score was significantly reduced from 1.96 $\pm$ 0.07 in the baseline to 1.22 $\pm$ 0.07 in the PSO condition ($p < 0.001$).

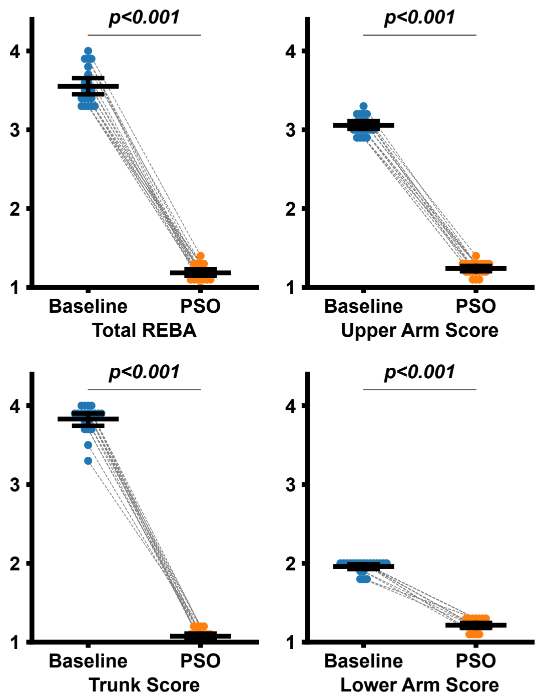


Figure 5. All REBA scores of participants across two conditions: baseline and PSO. All scores were significantly improved when using PSO optimization compared to the baseline. The scores of the same participant across conditions are connected by a dashed line. Error bars show the 95% confidence interval.

6. Discussion

The user study demonstrated a significant benefit of using the PSO algorithm to optimize the placement of the robot's end-effector within a VR environment. The implementation of the PSO algorithm resulted in improvements in all REBA scores. The total and the other REBA scores were significantly enhanced, reaching a value close to the ideal score of "1". During the human–robot collaboration, the PSO algorithm assigned proper placement locations to the robot to pass workpieces for assembly. Following the end-effector positions, the user was able to perform the task more ergonomically, reducing the risk of physical strain or injury.

Our proposed method was validated with people of different heights and handedness, demonstrating its potential for application to a wide range of users in the industry. However, it is important to note that the parameters of the framework might need to be adjusted according to the targeted tasks in each use case in the industry. Some factors need to be taken into consideration, e.g., the robot's movement limitations and the REBA threshold value. By making such adjustments, the placement of the robot's end-effector can be further optimized to provide more ergonomic collaboration between human workers and robots in industrial settings.

This framework provides several advantages, i.e., improving ergonomics and creating real-time safety measures, making it suitable for tasks, e.g., painting and polishing. The use of a VR platform and a non-intrusive motion capture device (i.e., the Kinect camera) reduces the cost of prototyping, training, and maintenance. This facilitates the process of deployment of human–robot collaborative tasks in real industrial settings. However, a limitation of this approach is that the user cannot feel the weight of the objects being passed by the robot. As a result, there might be differences in the user's posture in physical reality when dealing with heavier objects compared to what it is in VR. However, the differences are predicted to be small since the majority of objects used in assembly tasks are lightweight. Therefore, a direct implementation of our proposed framework from VR to physical reality is applicable to most industrial use cases.

7. Conclusions

MSDs are a significant concern in the industry since they are the leading cause of work-related injuries. These injuries are often caused by workers performing repetitive tasks in non-ergonomic positions. While using collaborative robots can partially reduce the non-ergonomic condition, an additional approach is to optimize the robot's end-effector during human–robot collaboration. In this work, we developed a solution that improves ergonomics by optimizing the robot's end-effector position using the PSO optimization algorithm. This algorithm takes into consideration the differences between the user's current ergonomics and the best possible ergonomics value, which is accessed using the REBA method. Through a human–robot collaboration user study in a VR environment, we demonstrated the potential of this approach to improve user ergonomics.

Future work will include validating our approach in a physical environment. The implementation of our proposed method can be further adapted to the needs of many industrial use cases. Once the implementation is deployed with workers in industrial settings, assessing user acceptability is important to further validate our proposed method.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy issues.

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