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A framework for human–robot collaboration enhanced by preference learning and ergonomics

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ABSTRACT

Industry 5.0 aims to prioritize human operators, focusing on their well-being and capabilities, while promoting collaboration between humans and robots to enhance efficiency and productivity. The integration of collaborative robots must ensure the health and well-being of human operators. Indeed, this paper addresses the need for a human-centered framework proposing a preference-based optimization algorithm in a human–robot collaboration (HRC) scenario with an ergonomics assessment to improve working conditions. The HRC application consists of optimizing a collaborative robot end-effector pose during an object-handling task. The following approach (AmPL-RULA) utilizes an Active multi-Preference Learning (AmPL) algorithm, a preference-based optimization method, where the user is requested to iteratively provide qualitative feedback by expressing pairwise preferences between a couple of candidates. To address physical well-being, an ergonomic performance index, Rapid Upper Limb Assessment (RULA), is combined with the user's pairwise preferences, so that the optimal setting can be computed. Experimental tests have been conducted to validate the method, involving collaborative assembly during the object handling performed by the robot. Results illustrate that the proposed method can improve the physical workload of the operator while easing the collaborative task.

1. Introduction

1.1. Context

One key aspect of Industry 5.0 is human–robot collaboration (HRC), which involves the collaboration between human workers and robots to increase efficiency, flexibility, and productivity [1]. In this context, it is crucial to evaluate the effects of HRC on the health of the human operator, taking into account both mental and physical aspects [2]. Assembly workers in the manufacturing industry, are at risk for physical and mental health problems which are common and costly for both workers and their employers [3].

This study focuses on collaborative assembly manufacturing tasks, where engaging in repetitive motions, adopting awkward body positions, and consistently exerting excessive force can lead to overloading the musculoskeletal system. Specifically, Work-related Musculoskeletal Disorders (WMSDs) are the most widespread work-related health issues in the EU, and stress and other psychosocial factors should also be taken into consideration when addressing these issues. Collaborative robots should be designed to improve the health and well-being of the human operator [4] through ergonomic design [5], which takes into account the comfort [6] and safety of the human operator when working alongside robots. By prioritizing the health and well-being of the human operator, HRC can be a positive force for improving working conditions and production performance [7]. Thus, assessing an individual's ergonomics to properly implement HRC frameworks is crucial. It is also important to consider the preferences [6] and motivations of the individual to create a working environment that is both physically and mentally conducive to productivity and well-being.

1.2. Aim of the work

The focus of this study is on optimizing the operator's posture to ensure comfort and minimize the risk of musculoskeletal disorders and

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to contemporarily match the operator's preferences. This means taking into account the human's preferred position while collaborating with the cobot to transfer objects, considering factors like reachability, ease of movement, and overall user satisfaction. In addition, ergonomics indexes, are also considered in the optimization procedure. Specifically, the RULA index has been adopted to minimize musculoskeletal disorders risk. With AmPL-RULA, it is possible to create a working environment that is optimized for both user ergonomics and their preferences, which may lead to increased satisfaction, motivation, and productivity, resulting in a more successful and efficient collaboration between humans and robots.

1.3. Related works

1.3.1. Preference-based optimization in HRC

Preference-based optimization is crucial in the HRC scenario because it allows for the customization of the collaboration between humans and robots and the optimization of the working environment, addressing the specific needs and preferences of the operator [8]. This can lead to increased satisfaction and motivation, resulting in improved productivity and overall success in the industry. In this way, preference-based optimization can be a valuable tool for designing and implementing HRC systems in Industry 5.0, as it allows for the integration of human skills and expertise in a way that is supportive of the operator's well-being and capabilities. Previous studies suggest that preference-based optimization is suitable for improving robot behavior. In [9] is presented a human-centric framework for robotic task learning and optimization based on a preference-based optimization (PBO) method. The method aims to incorporate a human's knowledge of a task (such as an operator's expertise in manual task tuning and execution) into a robotic system in order to optimize the performance of an industrial application. The approach has been implemented and validated for a robotic sealant material deposition task [10]. In [11] it is designed a preference-based learning approach where a reward function is modeled as Gaussian Process (GP) which learns using only human preferences, avoiding the implementation of human demonstration with high degrees of freedom. In this approach, instead of directly specifying the desired robot behavior, the human designer provides comparisons between demonstrated trajectories to guide the robot's learning process. The reward function is modeled using a GP and an active learning algorithm is used to efficiently learn the function from human preferences. The paper presents results from simulations and a user study that suggests it can effectively learn expressive reward functions for robotics tasks.

1.3.2. Ergonomics in HRC

Two main categories are considered to approach ergonomics in HRC [12]: *standard-based* and *cost-based*. The first one considers the standard ergonomic tools as driving criteria. In the second one, assumptions are made by researchers to indirectly achieve more ergonomic conditions for the workers, *e.g.*, joint torque/fatigue minimization, and human kinematics optimization.

Cost-based Approaches: These studies use several methods to measure the ergonomic cost, such as the distance of human joints from a neutral position [13], Bayesian inference [14], and torque induced by an external load [15–17]. More in detail, in [17], the authors propose a novel framework for HRC workstations that enable real-time adaptation to human factors such as dynamic loads on body joints, worker's handedness, task intent, and movement in the workspace. This framework aims to assist workers in performing the task by minimizing the effect of external loads on body joints. Here the cobot simultaneously adapts to user states, such as pose, overloading torques, manipulating hand, positional variations in the workspace, and task condition, by detecting the tools and parts in the workspace. In [18], the authors propose a method for controlling human–robot co-manipulation that takes into account the ergonomic requirements for the human co-worker implementing a whole-body dynamic model of the human to optimize for the position of the co-manipulation task in the workspace. In [19], a novel control approach for human–robot collaboration is presented that takes into account ergonomic aspects of the human co-worker during power tool operations. The appropriate robot motion that brings the human into a suitable ergonomic working configuration is obtained through an optimization method that minimizes the estimated overloading joint torques. The method includes several constraints, such as human arm muscular manipulability and safety of the collaborative task, to achieve a task-relevant optimized configuration.

Standard-based Approaches: a few observational methods have been implemented to improve physical ergonomics including Rapid Entire Body Assessment (REBA) [20], Rapid Upper Limb Assessment (RULA) [21], and Washington Industrial Safety and Health Act (WISHA) [22,23], to study ergonomics in the context of HRC as discussed in Lorenzini et al. [12]. The REBA method has been used to improve the comfort and safety of workers during collaborative tasks with robots, to design robot motion and plan sequences of actions, to predict and optimize human ergonomics during co-carrying tasks, to facilitate the human operator to assume a more convenient body configuration while operating on a bulky object held by the robot, and to set criteria for task allocation in a human–robot assembly operation. To achieve this goal, the body parts are separated into two independent groups: Group A (consisting of trunk, neck, and legs) and Group B (with upper and lower arms, and wrists). Each body part is analyzed, assigning a score depending on its level of flexion/extension, and then combined obtaining scores A and B. Furthermore, a score depending on the level of load/force is added to score A, while a Coupling score is added to score B. The A and B scores are combined to give a score C, using a scoring sheet, and finally, an activity score is added to give the final REBA score [20]. The RULA method has been used to position objects in a comfortable way for the user to operate them, to continuously invoke cooperative robot movements that meet the human partner's ergonomic postures, to plan robot motion in a way that is safer and more interpretable from the human point of view, to assign actions to either the human or the robot based on a human physical state indicator, and to generate robot plans that take into account human ergonomics and availability. The RULA score calculation is similar to REBA, and the body parts are categorized into two groups: group A (arm and wrist analysis) and group B (neck, trunk, and leg analysis). The force/load score, for each group, will be added only if the posture of the task is mainly static (i.e. held more than 1 minute), or if the action occurs 4 times per minute. Finally, the A and B scores are combined to give a score C, using a scoring sheet. The WISHA index has been used to generate robot plans that consider human availability, decisions, and ergonomics, taking into account the frequency, duration, and weights of tasks. The value is calculated through a series of questions related to different aspects of work tasks, workstations, and work environments, and then annotated on the WISHA Ergonomics Checklist. The WISHA index, in this context, refers to the overall score obtained from the checklist. The WISHA index is primarily used to identify areas of concern and prioritize interventions to reduce ergonomic risks in the workplace. Each of these ergonomic assessment methods provides a final score that helps determine the level of ergonomic risk associated with a particular task or workstation. The final score from REBA typically ranges from 1 to 15 or higher, while the final score from RULA ranges from 1 to 7 for each arm, with higher scores indicating higher ergonomic risk. The WISHA method, on the other hand, slightly differs from REBA and RULA, as it outputs two different scores:

- Weight Limit (WL), answering the question "Is this weight too heavy for the task?"
- Lifting Index (LI), answering the question "How significant is the risk?", being the sum between the object's weight and the WL.

The LI assumes positive values, detecting a potential risk if $1.0 < LI < 1.5$ and a significant risk if $LI > 1.5$. The goal is to design a job/task with a LI lower than 1.0. Other methods discussed include the Ovako Posture Analysis System (OWAS) and the Strain Index. More in detail, [24] adopted REBA to improve the workers' comfort and safety during a human–robot collaborative task. The human posture that minimized the score returned by REBA was computed and the robot pose was adjusted online to let the human perform the task in the optimized body configuration. Due to the discrete grading and the presence of plateaus in REBA, they approximated the discontinuous nature of the scores by a sum of weighted polynomials and optimized the weights to closely reproduce the score in the continuous domain. After that, they design a whole sequence of actions in the task [25]. In [26] an architecture for human–robot co-manipulation is proposed utilizing the RULA method to position the handled object in a way that is ergonomically comfortable for the user to operate. The RULA score was used to determine the most comfortable postures for the user. Additionally, the robot's admittance control feature allowed the user to easily adjust the position of the objects.

1.3.3. Object handling optimization in HRC

WMSDs are the largest category of work-related diseases in many industrial countries [27]. The main reason for MSDs is a non-ergonomic pose of the human handling an object, followed by heavy physical work and lifting [28]. Considering an HRC scenario, object handling often represents a critical stage of the task, specifically when a robotic device has to hand a component to the human collaborator. Several papers address this problem. In [29] human posture is enhanced by optimizing the human pose at time steps and for a whole collaborative task period. They predict the whole human posture by the hand pose through supervised learning (Nearest Neighbor map and Locally Weighted Projection Regression model) and correct the redundant problem by an inverse kinematic pose correction, making the hands of the full body pose match the hand poses. They estimate the load as well. Then, it is possible to calculate the REBA score which is going to affect the planning cost function and hence the robot movements during the task. In [24] the authors defined several cost functions (based on safety, acceptability, and task constraints) and constraints to find the optimal body posture during object handling. The main concern is about the definition of weights that are needed to build the final cost function which may be chosen to penalize one feature more than others, also depending on the specific task. A drawback of optimizing the body posture by directly minimizing cost functions is that some components cannot be oriented at will but that have constraints, such as those objects that if overturned will disassemble and fall due to gravity, but there exist many other particular cases which would imply to tune the cost function for every task. When adopting AmPL all these features are automatically taken into account, since they are intrinsic characteristics of the specific user. The parameters considered in the articles above (such as laterality, proxemics, distancing, orientation, and position) are tailored directly by letting the user with several tests and asking him/her to make preferences between two consecutive candidates. In [30] the authors have developed an efficient method for predicting the Object Transfer Point (OTP) in scenarios where a human is handing over an object to a robot. The method synthesizes an offline OTP calculated based on human preferences observed in a human–robot motion study with a dynamic OTP predicted based on the observed human motion. Interesting is the work presented in [14], where they formulate a process of learning a person's ergonomic cost as an online estimation problem via Bayesian inference. The robot can implicitly make queries to the person by handing them objects in different configurations and gets observations in response about the way they choose to take the object. Their goal is to make a robot configuration comfortable for the user and they assume that a comfortable posture is associated with an ergonomic one. However, this might not be the case, as the user prefers non-ergonomic postures. The user can feel comfortable in a position that is not necessarily ergonomically correct. Comfort is subjective and can vary from person to person. Ergonomic configuration, on the other hand, is based on scientific principles to reduce the risk of injuries and improve productivity. Conversely, our framework builds the human preferences based on actual preferences on a 5-point Likert scale rather than implicit demonstrations. Moreover, it moves away from ergonomically risky positions, yet leaving room for choice in customization and fine-tuning the final configuration. This is done also to account for variability and differences among people.

1.4. Paper contribution

Previous studies address the need for a framework that is based either on the preferences of the user (preference-based frameworks) 1.3.1 or on ergonomics (ergonomics-based frameworks) 1.3.2. With AmPL-RULA we want to address and comply with both these needs in a single adaptable framework: ergonomics and preferences are both considered in the optimization stage. Hence, this paper proposes an implementation of the AmPL algorithm to an HRC context, to optimize a cobot end-effector pose (or OTP) during an object handling task, both considering ergonomics (making use of a quantitative index, *i.e.*, RULA) and the preference of the specific user. The optimization of the pose is, therefore, the combination of the answers of the user (according to his/her feelings) and of the operator's posture (associated with the specific cobot's end-effector pose). Indeed, the novelties of the proposed approach are related to:

- an upgrade of the existing AmPL algorithm [31] through the inclusion of new features;
- the creation of an HRC framework that is both user preferences- (AmPL) and ergonomics- (RULA) based through a dedicated software tool;
- the implementation, testing, and evaluation of the proposed framework for optimizing a cobot end-effector's pose in a collaborative task.

The performance of the proposed framework have been evaluated in an HRC scenario for optimizing a cobot end-effector pose during an object handover task between the human operator and a collaborative robot. 20 volunteers participated in the experimental campaign, making use of the developed approach to independently optimize the end-effector pose of the robot in the collaborative task. Achieved results show that our framework suggested an end-effector pose that guarantees a low ergonomic risk while addressing the user's preferences.

2. Methodology

The proposed framework is schematized in Fig. 1. The user preferences are used in order to address the cognitive workload of the collaborative task (*e.g.*, user engagement, work-related stress, etc.), while an ergonomic index (RULA) is used to address the task ergonomics. Preference-based optimization is a semi-automated technique for solving black-box optimization problems, where the explicit mathematical expression of the objective function is either expensive or impossible to obtain [32]. In fact, searching for the optimum through manual programming and tuning is not efficient. Indeed, a semi-automated solution to guide the decision variables towards the optimum is desirable. In these cases, it is possible to use human preferences to guide the optimization process towards the optimal solution. Active Preference Learning [33,34] is addressed to find the global optimum of an unknown function using only the preferences of a human decision-maker. For the development of the framework in Fig. 1, we implemented the AmPL algorithm in [31], which is an upgrade of the method in [33,34], and we customized it in our tool in such a way to consider quantitative factors (*i.e.*, the ergonomics-related index) in the optimization process as well as an additional component called "penalization" function (aiming to avoid high-risk user postures). Compared to APL, AmPL

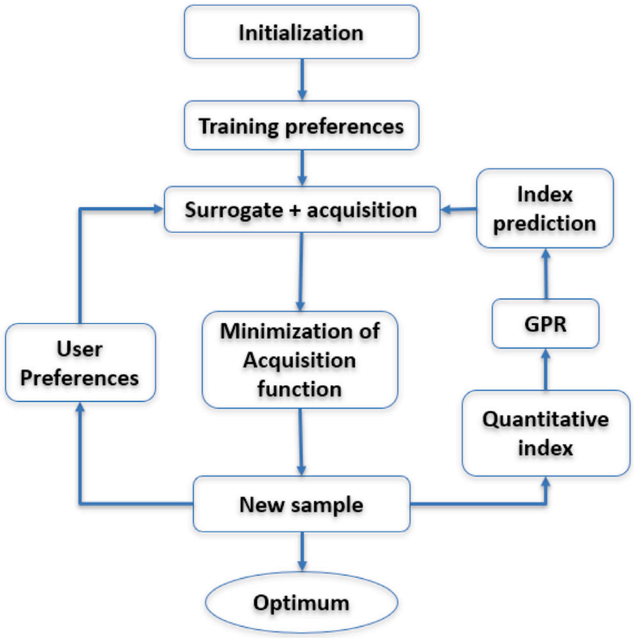


Fig. 1. Block diagram of the developed framework. The preference-based optimization (left side of the schema) and the quantitative index for the ergonomics analysis (right side of the schema) are combined to optimize the target collaborative task both considering the cognitive and physical workload.

introduces the 5-Likert scale in the preference between pairwise candidates and the uncertainty of the answer. It demonstrated to improve the performances and speed of convergence to the optimum [31]. In the following, the components of the proposed framework are described.

2.1. Active multi-preference learning

In AmPL, a black-box optimization problem is considered in which the objective function $f(x)$ is assumed to be non-accessible. Let $\mathbb{R}^n$ be the space of decision variables and x_1 and x_2 are two n-element vectors so that $x_1, x_2 \in \mathbb{R}^n$. Because the values of $f(x_1)$ and $f(x_2)$ cannot be quantifiable, only their comparison in the form of discrete feedback outcome p: $\mathbb{R}^n \times \mathbb{R}^n \rightarrow \{-2,-1,0,1,2\}$ and the corresponding certainty level c: $\mathbb{R}^n \times \mathbb{R}^n \rightarrow \{1,2,3,4\}$ are accessible. Then the overall *preference function* is a composition of the previously described outcomes and certainty levels and is defined as:

$$\begin{aligned} \pi : \mathbb{R}^n \times \mathbb{R}^n &\rightarrow \{-2,-1,0,1,2\} \times \{1,2,3,4\} \\ \pi(x_1,x_2) &= (p(x_1,x_2), c(x_1,x_2)), \end{aligned} \tag{1}$$

where:

$$p(x_1,x_2) = \begin{cases} \mathbf{-2} & \text{if } x_1 \text{ is “much better” than } x_2, \\ \mathbf{-1} & \text{if } x_1 \text{ is “better” than } x_2, \\ \mathbf{0} & \text{if } x_1 \text{ is “as good as” } x_2, \\ \mathbf{1} & \text{if } x_1 \text{ is “worse” than } x_2, \\ \mathbf{2} & \text{if } x_1 \text{ is “much worse” than } x_2, \end{cases} \tag{2}$$

and:

$$c(x_1,x_2) = \begin{cases} \mathbf{1} & : \text{not so sure}, \\ \mathbf{2} & : \text{quite sure}, \\ \mathbf{3} & : \text{sure}, \\ \mathbf{4} & \text{absolutely sure}. \end{cases} \tag{3}$$

Basically, the algorithm is based on the construction of two functions:

- a surrogate function $\hat{f} : \mathbb{R}^n \rightarrow \mathbb{R}$ of f which takes into account the preferences of the user. It basically tries to reproduce the answers of the user and make predictions for decision vectors not explored yet [31];
- an acquisition function $a : \mathbb{R}^n \rightarrow \mathbb{R}$ to be minimized, through global optimization, to get the next sample to be compared. It is the sum between the surrogate function and the exploration function. The latter one aims to avoid falling in local minima during the global optimization [31].

Here is the definition of the acquisition function:

$$a(x) = \frac{\hat{f}(x) - \min\{\hat{f}(x_i)\}}{\Delta\hat{F}} - \delta z(x), \tag{4}$$

where

$$\Delta\hat{F} = \max\{\hat{f}(x_i)\} - \min\{\hat{f}(x_i)\} \tag{5}$$

is the range of the surrogate function on the samples in X, δ is the gain used to balance the exploitation and exploration behaviors, and $z(x)$ is the exploration function, defined as:

$$z(x) = \begin{cases} 0 & \text{if } x \in \{x_1, \dots, x_N\} \\ \tan^{-1} \frac{1}{\sum_{i=1}^{N} \omega_i(x)} & \text{otherwise.} \end{cases} \tag{6}$$

$\omega_i : \mathbb{R}^n \rightarrow \mathbb{R}$ is defined by:

$$\omega_i(x) = \frac{1}{d^2(x,x_i)}, \tag{7}$$

where $d^2(x,x_i)$ is the Euclidean distance between x and x_i. The complete description of the algorithm is discussed in [31].

2.2. Enhancing AmPL to include quantitative indexes

As briefly discussed in Section 2, our general framework is designed to take into account also for quantitative indexes. This choice is made to account for those cases in which we can get supplementary data from the quantitative black-box optimization problem in addition to the user preferences. To account for these quantitative indexes (*i.e.*, to combine qualitative and quantitative optimization), the acquisition function in (4) is modified to:

$$a(x) = \frac{\hat{f}(x) - \min\{\hat{f}(x_i)\}}{\Delta\hat{F}} - \delta\frac{z(x)}{\Delta Z} + P(x) + \eta\,\kappa(x), \tag{8}$$

where:

$$\Delta Z = \max\{z(x_i)\} - \min\{z(x_i)\}. \tag{9}$$

The use of $\Delta\hat{F}$ in (5) and ΔZ in (9) allows making the exploitation and exploration contributions of the surrogate function (9) scaled between 0 and 1. Therefore, on the one hand, selecting $\delta > 1$ means preferring to explore the feasible space trying to find a more suitable set of parameters. On the other hand, if $\delta < 1$ means that the exploit behavior is prioritized to refine the optimum. The term $P(x)$ is devoted to the penalization of the acquisition function when the avoidance of a target zone of the feasible space is required (*e.g.*, w.r.t. safety criteria or poor performance). In fact, it may happen that, while performing the preference-based optimization, the user realizes that some zones of the feasible space are not optimal. In those cases, he/she can stress the point by manually weighting the function in that neighborhood, so that in the next iteration the new sample will be generated outside the penalized area. An illustrative example is depicted in Fig. 2 where 3 areas are chosen to be avoided within the next optimization step. The penalization function term $P(x)$ can be scaled based on the following definition:

$$P(x) = \sum_{i=1}^{N}\sum_{j=1}^{n} \frac{\zeta_1 w_i^j}{(x_i^j - x^j)^2 + \zeta_2}, \tag{10}$$

where:

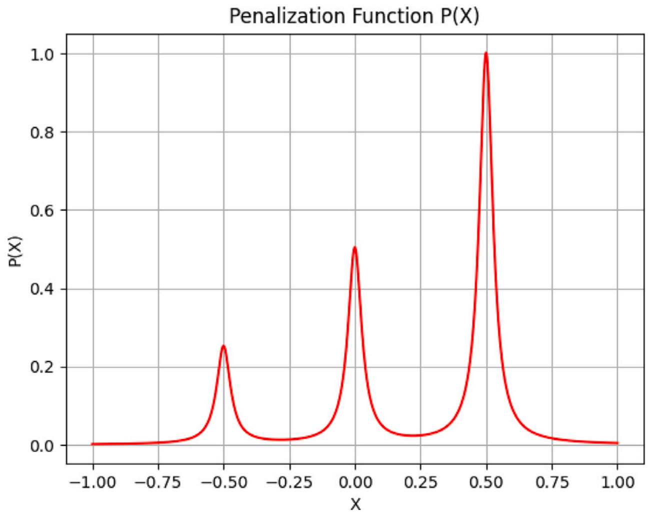


Fig. 2. This is an illustrative 1D example in which 3 penalized points are shown: $x_1 = -0.5$ with $\omega_1 = 0.25$, $x_2 = 0.0$ with $\omega_2 = 0.5$, $x_3 = 0.5$ with $\omega_3 = 1.0$.

- N represents the number of samples while n is the dimension of the decision vector;
- x_i^j represents the component j of the sampled decision vector i;
- x^j represents the component j of the variable x
- $\omega_{i,j}$ is the weight associated with the component j of considered sampled decision vector i. The higher the weight, the stronger the penalization;
- the term ζ_1 is needed to get the exact value of the weight when the distance $(x_i^j - x^j)^2$ is null;
- the term ζ_2 is needed to prevent the penalization function from assuming the value $\frac{0}{0}$.

The penalization function is a useful technique in optimization when the user gains knowledge of the system through experience and iterations. In this process, the user may recognize that certain values of the decision vector lead to worse results than others. Penalization can be applied to these values to discourage the optimization to suggest testing in such areas, improving the overall performance of the algorithm. The aforementioned penalization term is a new feature of the acquisition function (8) for the AmPL. The term $\kappa(x)$ in (8) is a quantitative factor to take into account for one or more quantitative criteria, and η is its related gain to modulate its impact inside the acquisition function (8). As previously discussed in Sections 1 and 1.3, ergonomics is a key aspect of Industry 5.0, and taking into account the physical comfort and safety of the operator is crucial in HRC. Hence, we decided to include ergonomics as a quantitative factor in the acquisition function for optimization purposes. With this approach, in the design and implementation of HRC in Industry 5.0, it is possible to create a work environment that is optimized for both user ergonomics and his/her preferences.

2.3. Ergonomics quantitative evaluation method: RULA

There exist many ways to evaluate ergonomics, all grouped into three main categories: Basic Methods, Direct Measurement Methods, and Observational Methods [35]. Direct Measurement Methods require expensive and impractical systems that are highly sensitive to human movements and often hinder users' activities. Therefore, the adoption of this technology in real-world scenarios is subject to certain limitations [12]. Observational Methods, on the other hand, have increasingly been used for assessing ergonomics. These techniques require an ergonomic expert to observe the workers performing the tasks and evaluate posture on different factors such as repetitive motion patterns, duration of work, and muscle force exertion [36]. Nevertheless, they are relatively inexpensive to carry out and can be used in different work situations without hindering the workers [12], but are only suitable for static or repetitive jobs and require the investigator to be trained before conducting the survey, making them expensive and include methods such as NIOSH lifting equation, REBA, RULA, OWAS, etc. Among the others, the Rapid Upper Limb Assessment (RULA) has been selected in this paper to evaluate the ergonomics of the collaborative task [37,38]. Regardless of industry, task type, and body balance, OWAS and REBA underestimate posture-related risk w.r.t. RULA [39]. Hence, to compute the RULA score, the body joint frames and positions of the user are acquired and processed. Then, the RULA score is then used in the optimization framework described in Section 2.2 as a quantitative index. A Gaussian Process Regression modeling (GPR) is implemented to map the RULA index w.r.t. the optimization variables and the human anthropometric parameters. Such modeling is then used in the proposed approach (Fig. 1) to predict the ergonomic index for optimization purposes (together with the user preferences), providing a prediction for the quantitative index $\kappa(x)$ in (8). GPR, in fact, is powerful in dealing with small datasets, also providing uncertainty measurement [40]. The employed modeling through the GPR allows for simplifying the application of the proposed framework in real industrial scenarios, avoiding the need for real-time user motion tracking for the calculation of the RULA score. In fact, after its training, the model can be employed in the optimization framework without the need for external sensors (*e.g.*, a vision system, or an IMU-based system for motion tracking).

3. Experimental assessment

The proposed framework has been applied to an HRC scenario, to optimize the cobot end-effector pose (composed by the three translations and rotations, so that $x = [x, y, z, \theta_x, \theta_y, \theta_z]^T$) during the object handover between the human operator and the collaborative robot, as shown in Fig. 5. In the following, the employed experimental material, the task, the participants, and the achieved results are detailed. The study is part of the European Project Mindbot [41] whose idea is to improve the worker's motivation and engagement within the cobot-worker interaction in a flexible and personalized way, to facilitate active and positive job experiences, thereby preventing negative experiences of anxiety or boredom and apathy.

3.1. Materials

In Fig. 3 the experimental setup is depicted, consisting of several components: (1) a tablet used to run the Fanuc software, (2) a PC running the Visual SceneMaker software to control the robot's movement, (3) a Microsoft Kinect camera used to track the operator's body joints for the calculation of the RULA ergonomic index (Section 2.3), (4) another PC (running the GUI, the AmPL algorithm 2.1 2.2, and the RULA real-time assessment algorithm), a Fanuc Cobot CRX-10iA/L (6 degrees of freedom cobot with a payload of 10 kg and 1249 mm of reaching), (5) a sub-assembly picked by the cobot and placed in front of the user according to the end-effector pose, a right-handed reference frame whose origin represents the midline between the feet tips of the user when executing the collaborative assembly, (6) pedals used by the operator to start/pause/stop the robot, and the (7) user's sub-assembly. The full assembly is shown in Fig. 4.

3.2. Task description

The optimization of the cobot end-effector pose during an object handover task between the human operator and the collaborative robot is considered. In particular, the parameters to be optimized are:

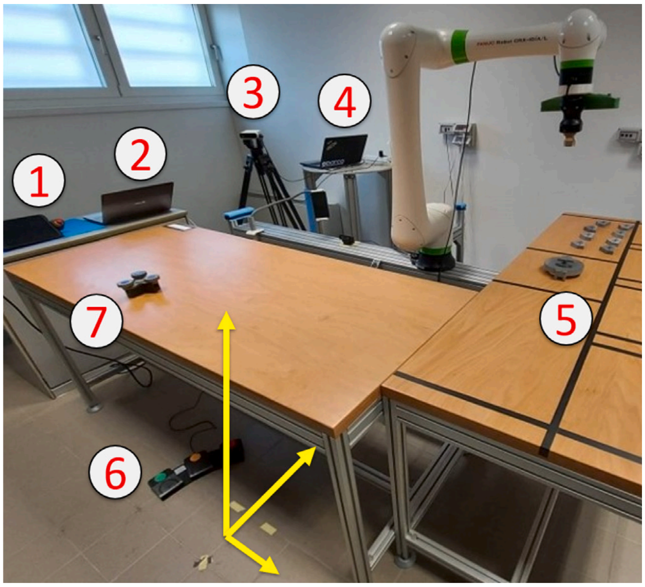


Fig. 3. Experimental setup showing the collaborative application used for the evaluation of the proposed framework.

- x, y, z: representing the relative 3D spatial coordinates of the end-effector concerning the base frame of the robot, represented in Fig. 5 by the white circle;
- θ_x, θ_y: representing the Euler angles w.r.t. the base frame. Note that since both the user and cobot sub-assemblies are axis-symmetric, we did not consider the third Euler angle θ_z in the optimization assuming that its variation during the experiment is not appreciable by the user, thus not affecting the preferences and the ergonomics index and therefore the optimization outcome.

The experimental procedure is composed of the following phases:

- training phase;
- optimization procedure;
- validation phase.

In the *training phase*, the expert operator will teach the user how to perform the experiments, such as assembling and disassembling the components, and how to express preferences. In the *optimization procedure*, two robot configurations (*i.e.*, end-effector poses) are tested by the user, *i.e.*, the best one so far (*i.e.*, the user's favorite one until the current optimization step), and the new one suggested by the optimization algorithm. These two configurations are evaluated by expressing a preference (*e.g.*, configuration A better than configuration B) based on the flowchart in Fig. 6, collecting such a preference using a GUI. As an exit criterion, the maximum number of optimization iterations is set equal to 30 (experimentally found to provide a good balance between exploration and exploitation in the considered experimental scenario; other exit criteria based on, *e.g.*, the satisfaction of the user might be designed). The δ parameter (regulating the trade-off between exploration and exploitation behavior in (8)) is defined so that:

$$\delta = \begin{cases} 1 & \text{if } N = 1 \\ 0.2 & \text{if } p_{\mathrm{h}} > 0 \\ \delta + 0.4 & \text{if } p_{\mathrm{h}} < 0 \wedge \delta < 2, \end{cases} \tag{11}$$

where $\wedge$ is the symbol for logical conjunction, $p_h = p(x_h, x_{best})$, x_h is the current set of optimization variables at the iteration h, and x_{best} is the best set of optimal variables so far (see Section 2.1). As shown in (11), the exploration parameter δ is initialized to 1. When the user selects "Much Worse" or "Worse", intending that x_h is better than x_{best}, δ is set equal to 0.2. This choice follows the assumption that the global optimum can be found in the neighborhood of x_h. Instead, if the user continues to prefer x_{best}, then δ increases by 0.4 and up to a maximum value of 2. This choice is made considering the case of a local minimum, for which the increasing exploration value allows to exit such a local minimum. Together with the preference of the user, the ergonomics index is used in the optimization procedure to evaluate the risk related to each configuration (see Section 3.3 for more details). In the *validation phase*, the user is asked to move manually (in manual guidance) the robot to the position that perfectly fits his/her preference to perform the target task, so that this robot pose might be compared with the optimum achieved by the proposed algorithm.

3.3. RULA-based quantitative index

To evaluate the ergonomics for static human posture, a real-time ergonomics assessment is implemented using body joint data gathered from a Microsoft Azure Kinect depth camera. The body joints data are fed into a ROS node which directly calculates the RULA score, which is an integer value representing a WMSD risk associated with the current pose of the operator. To obtain a reasonable and plausible estimation of the operator's body pose, he/she was requested to hold the position used to finalize the assembly task for some seconds (*i.e.*, 5 seconds), so that the ROS node prediction can stabilize to a constant integer value and compensate any hand deviation fluctuation. The RULA score is then

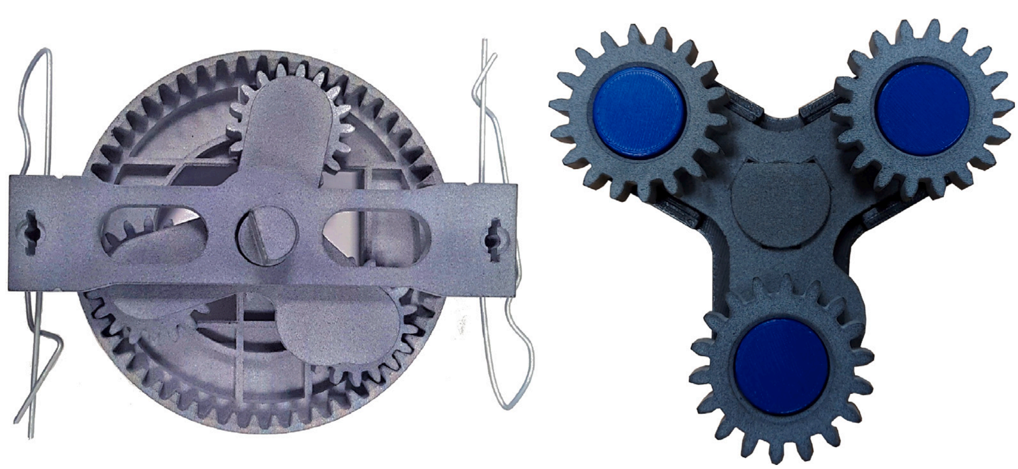


Fig. 4. On the left is drawn the complete assembly with a weight of 250 grams, on the right is the sub-assembly handled by the user (0.1 kg). The assembly is fully 3D printed and represents a planetary gearbox [42]. Note that the weight of the component handled by the user affects the RULA score: in our specific case, the value is lower than 4.4 lbs which translates to +0 in step 7 of the procedure to calculate the RULA score.

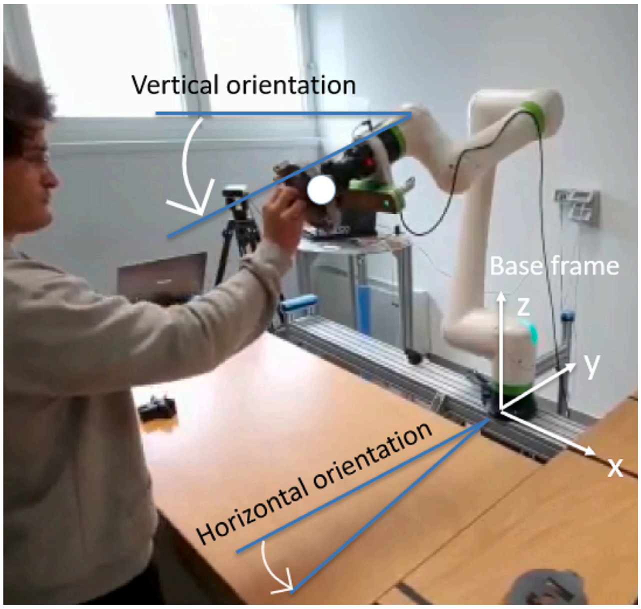


Fig. 5. Object handling pose: the user is completing the assembly task together with the robot. The white dot represents the static spatial position of the end-effector relative to the base frame, while the tilt is its orientation. These parameters are the optimization variables.

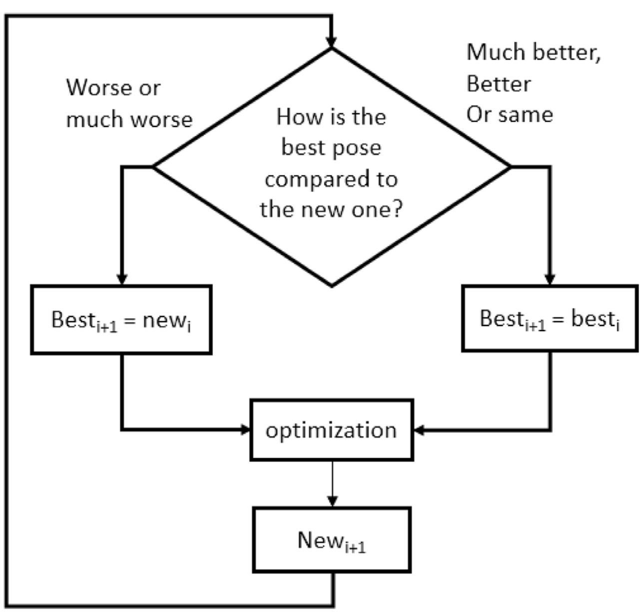


Fig. 6. Preference flowchart by the user for the update of the optimization procedure.

used as input to train the GPR and thus map the relationship between the robot position and the RULA score γ, obtaining the following relation:

$$\hat{\gamma}(\overline{x}) = GPR(x, y, z, \theta_x, \theta_y, h_H). \tag{12}$$

The parameter h_H refers to the user height so that the prediction of the RULA score $\hat{\gamma}(\overline{x})$ is related to the specific user, providing an accurate ergonomic index customized to the target operator. Indeed, the height of each user is used in the GPR to improve the modeling in (12). In such a way, after the model is trained, real-time body tracking is no longer required, simplifying the required setup for the use of the proposed framework. Indeed, $\overline{x}$ includes both the optimization parameters and the user height. As described in Section 2.3, the prediction of the RULA

Table 1
RULA score values based on the WMSD risk.

Score	Level of WMSD risk
1–2	Negligible risk, no action required
3–4	Low risk, change may be needed
5–6	Medium risk, further investigation
7	Very high risk, implement change now

Table 2
Optimization parameters.

	X [m]	Y [m]	Z [m]	θ_x [°]	θ_y [°]
Upper bound	0.5	0.3	1.75	90	45
Lower bound	−0.3	0.0	1.15	0	−45
Step	0.1	0.1	0.1	10	10
Range size	0.8	0.3	0.6	90	90

score $\hat{\gamma}(\overline{x})$ is used for optimization purposes by defining $\kappa(\overline{x})$ in (8) as follows:

$$\kappa(\overline{x}) = \begin{cases} 0 & \text{if } \hat{\gamma}(\overline{x}) < \gamma_{lim} \\ \frac{(\hat{\gamma}(\overline{x}) - \gamma_{lim})}{2} & \text{otherwise,} \end{cases} \tag{13}$$

where γ_{lim} is set equal to 5 so that, based on the WMSD risk [3] shown in Table 1, a posture is considered of medium risk from that score [21]. It has been therefore considered that, below that value, the user's preference takes precedence over the ergonomics index, in order to allow some personal freedom in choosing the robot pose.

The η gain in (8) has been set equal to 1 so that it weights the quantitative index $\kappa(\overline{x})$ as the other terms.

3.4. Experiment settings

In Table 2, the domain and the variation step of the optimization variables used in the experiments are reported. In particular, considering the *Step* parameter, it has been experimentally chosen to make the user perceive the change in the robot configuration (*i.e.*, if it is too small, no difference can be perceived by the user, see Fig. 7).

3.5. Participants

20 participants between 24 and 40 years have been involved in the experimental tests. 9 of them are right-handed, and 11 are left-handed.

In our study, we made a deliberate effort to ensure fairness by including both right-handed and left-handed individuals in a balanced manner. We did not solely rely on common social proportions but instead sought to achieve statistically similar representation of right-handed and left-handed participants. The mean participants' height is 171.5 cm, with a standard deviation of 8.5 cm.

4. Results and discussion

4.1. RULA modeling results

To determine the performance of the RULA modeling achieved by the GPR prediction ($\hat{\gamma}(\overline{x})$), the real-time RULA score $\gamma_{RT}(\overline{x})$ (computed through the measured user body configuration data) and the prediction $\hat{\gamma}(\overline{x})$ have been compared. Errors in the prediction of the RULA score affect the algorithm in two cases:

- $\hat{\gamma}(\overline{x}) < 5 \wedge \gamma_{RT}(\overline{x}) > 5$;
- $\hat{\gamma}(\overline{x}) > 5 \wedge \gamma_{RT}(\overline{x}) < 5$.

Table 3 shows the performance of the RULA prediction $\hat{\gamma}(\overline{x})$ in terms of mean error, the standard deviation of the error, and the percentage of cases in which the condition in (4.1) is met. The results were obtained by analyzing four datasets, each comprising 33 different poses of the

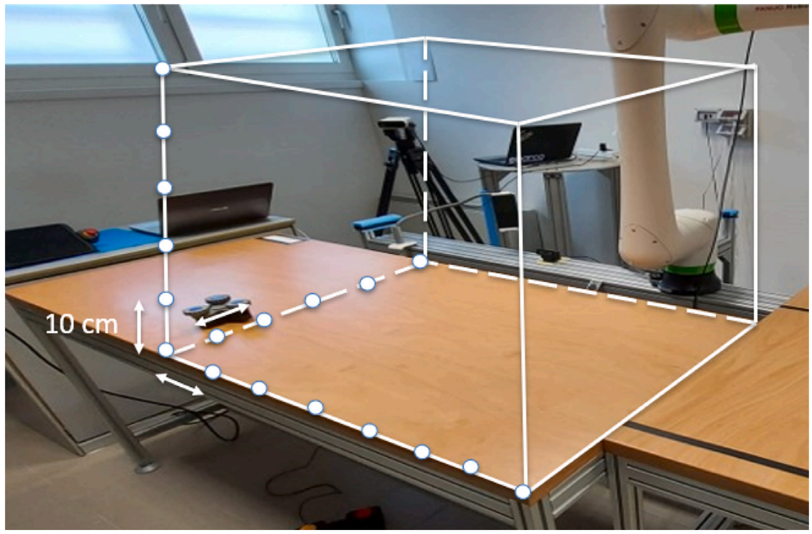


Fig. 7. End-effector spatial boundaries with discretization points.

Table 3
Achieved performance for the GPR modeling for the estimation of the RULA score.

Parameter	Value
Mean error	0.9
Standard Deviation of the error	0.8
% of wrong classification	15.1

Table 5
Mean of the error magnitude of the spatial (x, y, z) and spherical (θ_x, θ_y) components.

	EM(x, y, z) [m]	EM(θ_x, θ_y) [°]
Mean	0.12	12.19

Table 4
Mean error ($\overline{e}$), standard deviation ($\overline{\sigma}$) and mean percentage error for each variable.

	x [m]	y [m]	z [m]	θ_x [°]	θ_y [°]
$\overline{e}$	0.06	0.05	0.09	7.66	11.65
$\overline{\sigma}$	0.07	0.03	0.06	11.18	7.73
MPE	7.18%	15.02%	15.25%	8.51%	12.94%

collaborative robot and recording the related real-time RULA score of the user's posture. These four datasets were chosen to account for height variability among individuals to improve the fitting of the GPR model. The accuracy of the GPR classification method is considered sufficient for the optimization purposes in this paper. In fact, after testing a set of optimization parameters, the RULA index is measured and updated in the optimization surrogate function. This way, even an incorrect prediction is corrected, and the optimization surrogate model is improved.

4.2. Optimization framework results

The results are presented in terms of the pose error between the optimum obtained using the developed framework and the one set manually by the user through the manual guidance of the robot (as described in Section 3.2). The results are reported in Table 4.

The Mean Percentage Error (MPE) is calculated considering the considered ranges of the variables as in Table 2. Therefore, as a matter of example, the MPE of the variable y is a bit higher than the other variables because of its range and step. The y variable may assume only four values: {0.0 0.1 0.2 0.3}.

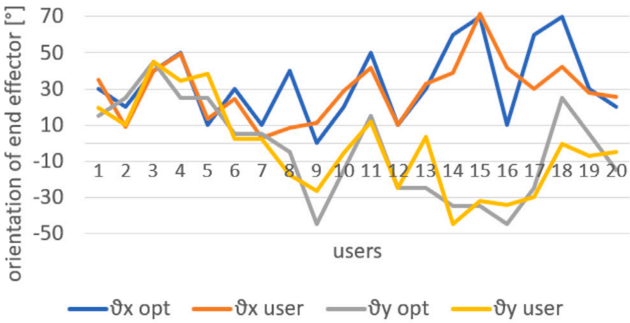
Another way to understand the results is to calculate the error magnitude (EM) taking into account the spatial components all together (x, y, z) and the two angular components all together (θ_x, θ_y) as in Table 5.

Even though the number of iterations within a single experiment is relatively low considering the number of parameters to be optimized [31–34], they are sufficient to reach an admissible configuration of the robot with respect to the user expectations. As a matter of fact, according to the performance results presented in Table 4, the algorithm's error for each variable was found to be lower than the corresponding problem resolution specified in Table 2. These thresholds were presented in 3.4 and indicate the level below which users tend to face difficulty in expressing their preferences. In addition, the majority of participants found it challenging to differentiate the optimal choice towards the conclusion of the study.

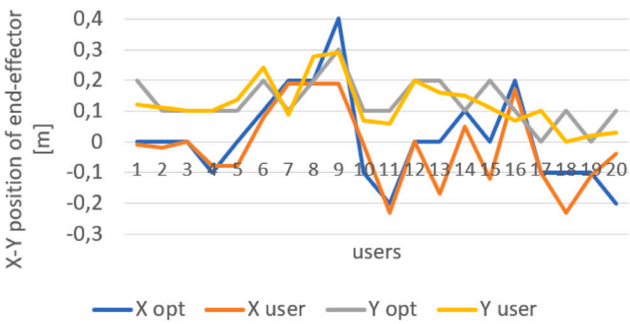
In Fig. 8 the solution found by the proposed approach and the pose selected by the user through manual guidance are compared. The results, together with the acceptable errors described in Tables 4 and 5 suggest that the algorithm was able to recognize the hand preference (laterality) of the users for the majority of the experiments, as well as proxemics, distancing, orientation, and position as previously discussed in Section 1.3.3. Fig. 9 shows the RULA score, describing the quality of the assumed posture of the different users in correspondence with the optimum obtained by means of the proposed optimization framework compared with the score obtained manually by the user. Indeed, it can be seen that what the users prefer regarding perception/comfort during the optimization procedure to perform the target collaborative task is also ergonomic. This is also highlighted by looking at "RULA opt" in Fig. 9, which is below the medium risk line for all the users. This result is consistent with the findings obtained through manual guidance, which fully align with user preferences. The similarity between the RULA score associated with the pose selected through manual guidance by the user and the one related to the optimal pose found by the proposed approach is supported by the small errors in Table 4. This can be explained by considering that if the two poses are close, the posture assumed by the user should also be similar.

4.3. Discussion

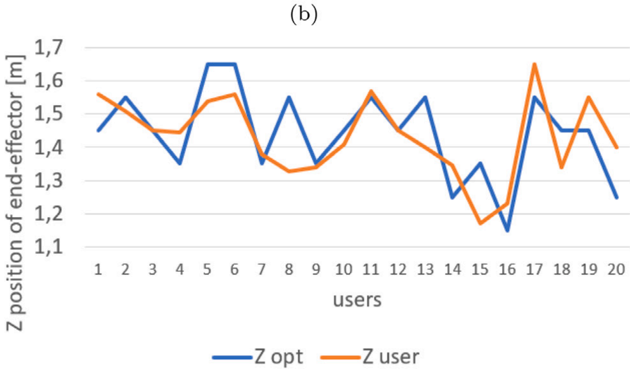
As highlighted in the achieved results, the proposed framework is capable of guaranteeing a robot pose that both satisfies the expectations of the user (Fig. 8) together with the safety requirements provided by the RULA score (Fig. 9). As can be seen in the definition of the RULA cost function in (13), the proposed approach aims to avoid those robot



(a)



(b)



(c)

Fig. 8. These three graphs compare the optimal solution of the algorithm ("opt") with the pose selected by the user through manual guidance ("user") whose errors are shown in Table 4. The participants are represented on the horizontal axis **("users")**. The first graph shows the orientation of the end-effector given by θ_x [°] and θ_y [°], which are respectively the vertical and horizontal orientations. The second graph represents the position of the end-effector along the X and Y axis [m], while the third one shows the end-effector position along the Z axis [m].

configurations that cause the operator to work in a high-risk posture. Each user has selected a configuration of the robot with a RULA score associated with a low WMSD risk. Those results are strictly connected to this experimental campaign and should not be taken for granted in other types of operative scenarios. For instance, other conditions may lead to searching for a posture that is not comfortable for the user [43]. In fact, postural comfort and ergonomics are different in that: while ergonomics focuses on postural parameters to guarantee the safety and well-being of users and prevent health problems, comfort looks at a wider range of factors such as cognitive, physiologic, and environmental factors [44]. Additionally, not all users minimized the RULA completely. Some preferred a pose with a related RULA score equal to 4, demonstrating that the most comfortable posture may be different from the ergonomically optimal posture. Some users have commented that, during the experiment, they had difficulties in understanding how to express preferences with the admissible answers and

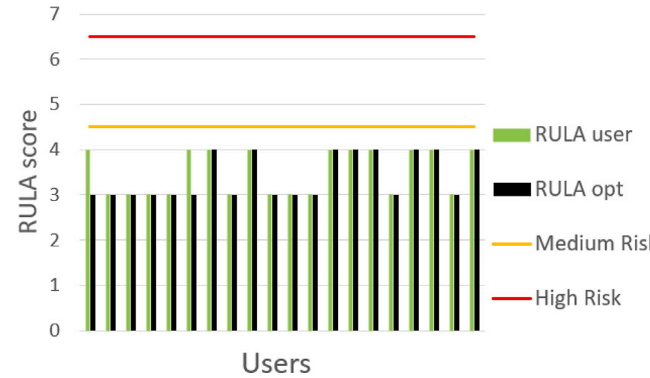


Fig. 9. Computed RULA score for the human posture assumed by adopting the optimum robot configuration provided by the proposed approach for each user ("RULA opt") vs the one resulting by adopting the robot configuration freely selected by the users ("RULA user"). The two horizontal dashed lines represent the limits of medium (yellow) and high (red) risks of WMSDs related to the assumed posture [21]. As can be seen, the "RULA opt" value of each user is below the medium risk line, representing that the users, during the completion of the task, intrinsically optimize the ergonomics, converging to a more comfortable posture.

relative level of uncertainty. In fact, sometimes, it seems that the users associate the level of certainty with the level of intensity of the answer. They reported that when they answer with a strong choice, like *Much Better* or *Much Worse*, they find the possibility of associating it with a low certainty level unnatural. As a consequence, they are more prone to answer with *Much Better* or *Much Worse* with the highest level of certainty. Moreover, some users commented that the number of choices is too much in making a preference and trying to combine two of them made it difficult to express personal feelings.

5. Conclusions

The proposed optimization framework addressed the problem of combining preference-based optimization and ergonomic-based optimization to set up a collaborative application. To the best knowledge of the authors, this is the first contribution combining these two techniques to guarantee that the task is optimized taking into consideration both the user preference and the task ergonomics.

The reported results show the potential of this approach, allowing the selection of the best set of optimization parameters in the collaborative task while guaranteeing the best ergonomic conditions for the operator. In such a way, qualitative optimization and quantitative metrics are effectively combined into the proposed optimization algorithm.

Future work will focus on the limitations discussed in Section 4.3. One potential approach to address preferences and certainty issues is to introduce constraints on the levels of certainty. Specifically, we can associate the extreme choices ('Much Better' and 'Much Worse') with the only possibility of selecting between 100% and 75% certainty. In contrast, for the intermediate choices ('Better,' 'Worse,' and 'Same'), users can be given the flexibility to express their level of certainty at 75%, 50%, or 25%. By implementing this adjustment, we aim to alleviate the users' confusion about associating intensity with certainty and also reduce the burden of making preferences when combining multiple choices. An improved GUI will be also designed so that a natural interaction will be established between the human and the optimization framework, also considering voice commands/feedback. Dynamic tasks will be also considered to extend the usage of the proposed framework to these scenarios. In addition, we will explore the possibility of implementing a dual classification approach. This would involve training the model on data from various individuals and optimizing the parameters accordingly. Once the model reaches a sufficient level of training, we could consider semi-automating the process by classifying the user based on multiple criteria, including facial recognition, limb lengths, or even robotic skills. This would enable us to enhance the optimization process and tailor the user experience more effectively. Finally, an online implementation of the framework (*i.e.*, including online monitoring and fast adaptation to new operative conditions) will be developed.

CRediT authorship contribution statement

Matteo Meregalli Falerni: Conceptualization, Data curation, Investigation, Methodology, Validation, Visualization, Writing – original draft. **Vincenzo Pomponi:** Data curation, Investigation, Methodology, Software, Validation, Writing – original draft, Writing – review & editing, Visualization. **Hamid Reza Karimi:** Supervision. **Matteo Lavit Nicora:** Supervision. **Le Anh Dao:** Conceptualization, Methodology, Supervision, Writing – original draft. **Matteo Malosio:** Supervision, Writing – original draft. **Loris Roveda:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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