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Ergonomically optimized path planning for industrial human-robot collaboration

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Abstract

This paper focuses on improving the ergonomics of industrial workers. It addresses the critical implications of poor ergonomics, which can lead to musculoskeletal disorders over time. A novel methodology for a path-planning algorithm designed for human-robot collaboration was introduced to tackle this challenge. The algorithm's essential contribution lies in determining the most ergonomic path for a robot to guide a human's hand during task execution, facilitating a transition toward an optimized body configuration. The algorithm effectively charts the ergonomic path by adopting a Cartesian path planning approach and employing the cell decomposition method. The methodology was implemented on a dataset of ten individuals, representing a diverse group of male and female subjects aged between 20 and 35, with one participant being left-handed. The algorithm was applied to three different activities: "stacking an item," "taking an object from a shelf," and "assembling an object by sitting over a table." The results demonstrated a significant improvement in the REBA score (as a measure of ergonomics condition) of the individuals after applying the algorithm. This outcome reinforces the efficacy of the methodology in enhancing the ergonomics of industrial workers. Furthermore, the study compared the performance of A* with three heuristic functions against Dijkstra's algorithm, aiming to identify the most effective approach for achieving optimal ergonomic paths in human-robot collaboration. The findings revealed that A* with a specific heuristic function surpassed Dijkstra's algorithm, underscoring its superiority in this context. The findings highlight the potential for optimizing human-robot collaboration and offer practical implications for designing more efficient industrial work environments.

Keywords

Human-Robot Collaboration, Ergonomics, Path planning, REBA, FABRIK

Introduction

In collaborative scenarios, it is a common practice to adjust the positioning of tools or objects to facilitate accessibility and enhance workflow. This behavior is observed in various situations, such as a mechanic ensuring tools are within easy reach of their assistant or a sergeant who asks for a specific tool to hand over to him while he is in operation. Similarly, in everyday encounters, people may modify the location of objects within reach of another person. In various contexts, these collaborative adjustments demonstrate an inherent recognition that optimizing the positioning of the tool can enhance interactions, promote smooth collaboration, and boost task efficiency (Strabala et al. 2013).

The potential of human-robot collaboration holds significant promise for revolutionizing workplace safety, enhancing ergonomics, and safeguarding worker health within industrial settings. This potential is especially pertinent in addressing the challenges associated with poor ergonomics resulting from suboptimal postures during tasks involving repetitive motions. Integrating robots into such tasks offers a collaborative approach that can effectively mitigate workplace hazards, alleviate physical strain experienced by workers, and substantially reduce the risk of injuries.

It is essential to recognize that repetitive motions, prolonged static positions, and inadequate body positioning are known contributors to the development of work-related musculoskeletal disorders (WMSD), as highlighted by Punnett and Wegman (2004). In the context of this manuscript, it's essential to provide a concise working definition of how these disorders are directly linked to ergonomics. In essence, ergonomics encompasses the science of optimizing workplace conditions and task design to minimize the physical stress and strain imposed on workers, thereby preventing the onset of WMSD.

In line with Lorenzini et al. (2023) recent findings (2023), the combination of these factors underscores the critical importance of harnessing human-robot collaboration to enhance the overall well-being of industrial workers. This collaborative approach addresses the negative consequences of poor ergonomics and actively promotes a safer work environment tailored to workers' unique needs and challenges in various industrial settings.

Accordingly, motion planning is crucial in automating collaborative robots to enhance ergonomic interactions

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with human partners. Collaborative robots, or cobots, are designed to work alongside humans in shared workspaces to improve productivity and reduce physical strain. Practical motion planning algorithms are essential for cobots to navigate and perform tasks in a manner that optimizes ergonomics for human partners. By incorporating human-centric considerations into the motion planning process, such as joint limits, reachability, and workspace constraints, cobots can adapt their movements to ensure safe and comfortable collaboration with humans. These collaborative adaptations reflect a natural understanding that optimizing the tool's placement can streamline interactions, foster seamless collaboration, and improve task efficiency in diverse contexts (Lasota and Shah 2015).

This paper presents a novel approach that evaluates the posture of the human partner, suggests ergonomic adjustments, and guides him/her towards improved posture by strategically relocating tools onto their hands. The paper's motivation can be separated into two distinct reasons. First, it acknowledges that the risk of Musculoskeletal Disorders (MSDs) is shaped by both the inherent risk level of the posture and the duration of exposure to that posture. In tasks that involve repetitive actions over extended periods, the cumulative time spent in non-ergonomic postures becomes significant, amplifying the overall MSD risk. Second, in certain industrial tasks that demand continuous contact with the workpiece, such as assembling a piece that cannot be removed from the tool, initiating work in non-ergonomic postures is often unavoidable due to the nature of the task. Hence, transitioning periodically to more ergonomic postures becomes crucial for minimizing the risk of musculoskeletal strain or discomfort. Although these transitions constitute a small fraction of the total task time, their repetitive occurrence throughout the workday substantially impacts worker comfort and long-term health. Consequently, the paper's motivation is firmly grounded in the mission to safeguard worker well-being and alleviate the potential for musculoskeletal disorders within industrial settings.

In the following Section, Related Works presents various research works that explored the intersection of human-robot collaboration and ergonomics optimization. Section Problem Formulation describes the problem statement and two main parts of the study: determining the ergonomic condition of the human operator's initial posture based on established ergonomic assessment methods and defining a suitable path that ensures the ergonomic condition of the human operator, given the robot's workspace restrictions and allowable movement locations. Section Methodology integrates ergonomic principles with robot motion planning techniques to foster improved ergonomics, increased productivity, and reduced risks of musculoskeletal disorders. Section Results and Validation discusses the experimental results of the proposed methodology. Finally, the conclusion and future work section summarizes the paper's contribution and suggests future work to enhance the efficacy of the developed approach.

Related Works

Human-robot collaboration has witnessed significant advancements in recent years, with a growing focus on optimizing the ergonomic aspects of these interactions. This section presents a comprehensive review of related works that explore the intersection of human-robot collaboration and ergonomics optimization.

Busch et al. (2018) addressed the challenge of human-robot collaboration by treating it as a combined task and motion planning problem involving multiple agents. The method incorporates ergonomic cost as a differentiable model called dREBA, using it as a cost function in the Logic-Geometric Program (LGP) formulation. LGP combines symbolic action sequences and smooth system motion optimization, optimizing them jointly with control costs to achieve improved ergonomic outcomes through simulated experiments, a real-world robot experiment, and a user study while considering synchrony and concurrency of behavior.

Nejadasl et al. (2022) and Yazdani et al. (2022) proposed methods to optimize worker posture. This deep neural network model accurately approximates tabular ergonomic assessment methods, enabling the derivation and recommendation of safe and ergonomic postures by solving the task constraints optimization problem using NeuroErgo as the posture cost function.

Peternel et al. (2017, 2019) introduced two innovative approaches to enhance human-robot collaboration during co-manipulation tasks. The first approach utilizes a whole-body dynamic model of the human to optimize the position of the co-manipulation task in the workspace, minimizing overloading joint torques and ensuring good manipulation capacity. The second approach involves selectively monitoring and managing human muscle fatigue levels using machine learning techniques to modify task execution configurations and the direction of the endpoint force to minimize fatigue. The proposed method can increase productivity and provide safer and more ergonomic working conditions for the human coworker in real-world scenarios. To verify the efficacy of their methods, they conducted experiments on two collaborative tasks (polishing and drilling) under varying conditions.

Kim et al. (2021, 2018) proposed two approaches for ergonomic improvement through human-robot collaboration. The first work presents a novel control approach to human-robot collaboration that considers the ergonomic aspects of the human co-worker during power tool operations. In comparison, the second work proposed a wearable feedback interface to improve human ergonomics in the execution of heavy or repetitive industrial tasks by providing vibrotactile feedback guidance to minimize overloading efforts.

Lorenzini et al. (2019) proposed a whole-body fatigue model to evaluate the effect of overloading torque induced on joints by light payloads over time, which is integrated into a human-robot collaboration framework to optimize body posture guided by robot assistance when fatigue overcomes a threshold in any joint, thus reducing the risk of injuries caused by excessive fatigue accumulation.

Merikh-Nejadasl et al. (2021) proposed an optimization algorithm, recommending an optimal ergonomic posture for accomplishing a task in an industrial setting. For this, ergonomically dangerous and uncomfortable poses are first changed heuristically to more ergonomic ones. To evaluate the ergonomics, the REBA method is used. The feasibility of each obtained posture is then verified by an inverse kinematics algorithm (FABRIK). These two steps are performed iteratively until the optimal ergonomic pose of the worker is obtained, which corresponds to the pose with the lowest REBA score.

Shafti et al. (2019) presented a novel approach to human-robot interaction focused on optimizing ergonomics. Utilizing an RGB-D camera for real-time monitoring of human joint angles, the algorithmic framework identifies six main causes of low ergonomic states. It controls the cooperating robot to adapt to the environment accordingly. The proposed approach ensures that the user's posture is returned to an ergonomic optimum by continuously observing a human user's posture and employing appropriate cooperative robot movements. This method effectively corrects non-ergonomic postures by applying translations or orientation adjustments in the upper body frames, reducing the Rapid Upper Limb Assessment (RULA) score.

Despite their focus on enhancing human ergonomics in human-robot collaboration scenarios, none of the mentioned works specifically tackled the critical issue of motion planning, which involves optimizing the robot's movements to meet these ergonomic requirements effectively.

Figueredo et al. (2021) addressed the challenge of planning a robot configuration and grasp to optimize forceful human-robot collaboration tasks while minimizing human muscular effort and ensuring interaction stability. The researchers developed a planner that predicts human muscular effort based on combined kinematic configurations and task forces, estimates human body kinematics to minimize effort, and ensures stable robot grasp and joint torques. Experimental results demonstrate the planner's effectiveness in reducing human muscular load, achieving a significant reduction compared to user-based object pose selection in the tested tasks. Nevertheless, the aforementioned study restricts their comfort assessment by relying solely on subjective ratings or utilizing only two specific musculoskeletal models of the human arm. This approach lacks a mathematical modeling methodology to evaluate human comfort in tasks involving human-robot collaboration (HRC) and real-time computation.

Franceschi et al. (2022) addressed the challenge of role arbitration between humans and robots in physical Human-Robot Interaction by modeling it as a Cooperative Differential Game, defining a law based on interaction force. The proposed framework effectively manages leader-follower transitions, enables high-performance trajectory tracking, and accommodates various modules and robot behaviors. Kim et al. (2019) have primarily focused on dynamically adapting workstations to the unique needs of workers, primarily in high-volume production facilities. These approaches have used optimization-based planning strategies to determine the robot-tool attitude based on a predefined set of task-dependent muscle groups and evaluated ergonomics through a cost function. However, they fall short in accounting for real-time prediction and planning of human comfort or the continuous movement of the robot/tool during operation.

Vogel et al. (2017) presented a comprehensive system setup and configuration essential for ergonomic integration into human-robot collaboration. It introduces a projection- and camera-based technology that enhances safety creates dynamic safety spaces, and facilitates interactive communication. This technology ensures human safety and provides worker assistance and information visualization, primarily demonstrated through active visual tracking. Tassi et al. (2022)s proposed the framework combines vision techniques for human action recognition and image classification with Augmented Hierarchical Quadratic Programming (AHQP) to improve the robot's reactivity and human ergonomics during collaboration. The experiments confirm enhanced ergonomics and usability, which are critical for reducing musculoskeletal diseases and building trust in automation. Furthermore, Faber et al. (2015) addressed the prerequisites for seamless human-robot cooperation in industrial assembly processes, outlining technical, human-centric, and normative criteria. It presents an early implementation of this concept using a cognitively automated assembly system, emphasizing the potential for increased manufacturing efficiency through effective human-robot collaboration while highlighting the need for addressing standards and practical management aspects.

Problem Formulation

The problem formulation in human-robot collaboration for a drilling or similar industrial task, as depicted in Figure 1, involves a human operator standing and holding a tool while performing a stationary task. In this scenario, a collaborative robot is positioned in front of the human, ready to assist and collaborate. However, suppose the human operator is tracked in an uncomfortable or non-ergonomic posture during the task, such as bending forward. The robot must intervene and correct the tool's location in that case. The objective is to get the human operator to continue the work in a more ergonomic posture, minimizing the risk of musculoskeletal disorders and promoting a safer and healthier working environment.

To address this problem, a combination of four different modules is used, as depicted in Figure 2. The interaction between the human operator and the collaborative robot in this context involves sensing technologies, analysis, planning, and robot execution. It should be noted that the focus is to provide the planning algorithm for the robot to improve the human partner's ergonomics; in this context, improved ergonomics means a reduced REBA score (The details are described in Section "Ergonomic Evaluation"). In the items below, each part is described briefly. And in the following sections, the details are provided.

1. **Ergonomic Evaluation:** Vision systems or wearable sensors are employed to continuously monitor the posture and movements of the human operator in real-time.
2. **Analysis Module:** The data collected by these sensors is subject to processing within an analysis module consisting of two submodules. One submodule is dedicated to modeling the shared workspace between the human and the robot, specifically in the form

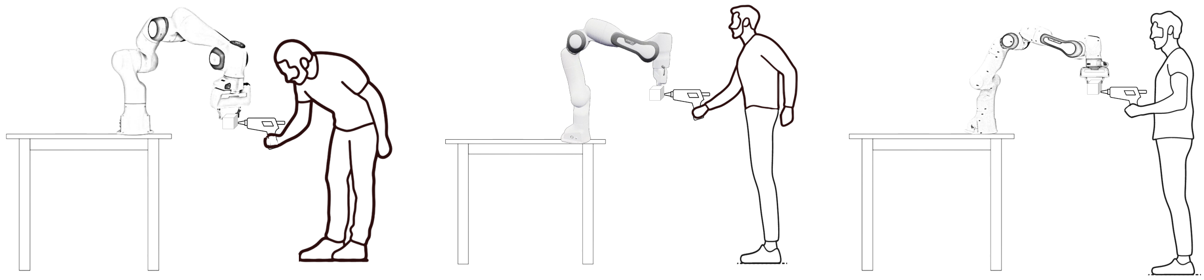

Figure 1. The human standing in front of the collaborative robot (Franka Emika Panda), on top of a table with 0.845 meters in height and ready to do the power tool task in the industry. The initial posture is detected on the left, which is the person doing the task in a non-ergonomic posture. In the intermediate step, the robot changes the workpiece, and the human hand transitions. Finally, on the right is the person standing in his most ergonomic posture.

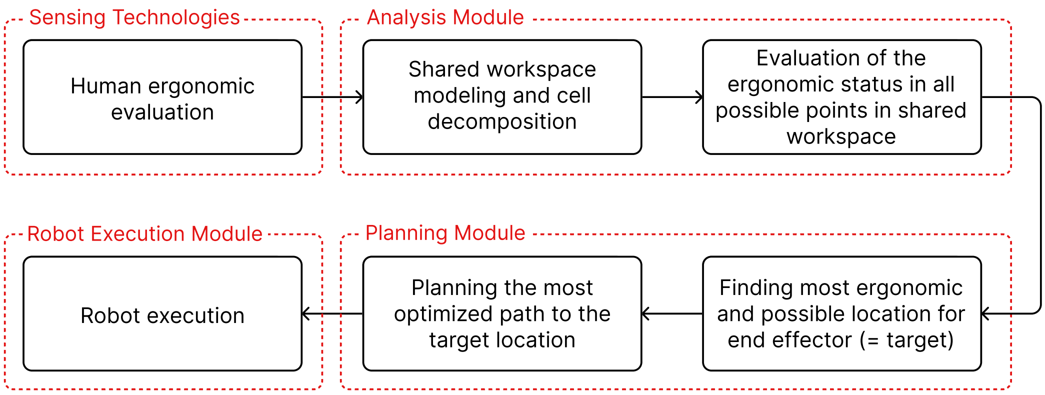

Figure 2. The methodology architecture contains several modules, starting with the evaluation module and then the analysis, planning, and execution modules.

of a gridded workspace (further elaborated in the Methodology section).

The second submodule employs an ergonomic assessment tool known as the Rapid Entire Body Assessment method (REBA) (Hignett and McAtamney 2000) in this study. It estimates the ergonomic condition of the human's posture when both the robot and the human's hand are positioned within each grid node. In this context, a more ergonomic posture is identified as the one with a lower REBA score."

This means that the submodule uses the REBA method to evaluate how ergonomically comfortable the human's posture is when the human and robot are at different positions on the grid. A lower REBA score indicates a more ergonomic and comfortable posture.

3. **Planning Module:** The nodes in the grid, which are associated with REBA scores generated by the prior module, are arranged in ascending order of their REBA scores. In the planning module, the path is determined from the initial configuration to a node characterized by a lower REBA score, all while taking into account the task requirements and the specified ergonomic criteria.
4. **Robot Execution Module:** In conclusion, the collaborative robot employs control algorithms to enact changes, which could encompass adjusting the robot's position, orientation, or force application. The nature of these adjustments depends on the particular requirements of the task and the ergonomic standards in place. The central objective of the robot is to assist and guide the human operator in achieving a more ergonomic posture. Importantly, it's worth highlighting that there is no physical contact between the robot and the human hand; instead, the robot solely manipulates the position of the tool that the human is using.

Through proactive intervention to adjust the posture of the human operator, the collaborative robot enhances ergonomics, diminishes the likelihood of injuries, and boosts overall task performance and efficiency. As a result, it mitigates the risk of sick leaves or absenteeism due to Work-Related Musculoskeletal Disorders (WMSDs) in the future.

The problem entails two main challenges: first, determining the ergonomic condition of the initial posture of the human operator based on established ergonomic assessment methods, such as the Rapid Entire Body Assessment (REBA). The ergonomic condition will be critical in guiding the subsequent path-planning process. Second, considering the robot's workspace restrictions and allowable movement locations, the task is to compute a suitable path that ensures minimal interference with the human operator and the surrounding environment. This path should enable the robot to approach the human operator in a way that minimizes potential ergonomic risks and guarantees a safe and efficient relocation of the workpiece.

To fully define the problem statement, the optimization problem mathematically is addressed in the following. P_{start} is a vector representing the pose of the point on the shared workspace where the human operator is holding the tool. P_{goal} similarly is a vector representing the pose of the most ergonomic position for the tool, based on the allowable movement locations of the robot. $D(P_i, P_j)$ is the Euclidean distance between points P_i and P_j. $C(P_i)$ is a cost function that quantifies the ergonomic condition of a given posture while the human hand is located in point P_i. In this study, C or cost function is the REBA score, which should be minimized and described later in Section *Ergonomic Evaluation*. w_d is the weight assigned to the Euclidean distance goal. w_c is the weight given to the ergonomic condition goal.

The optimization goal is to find an optimal ergonomic and shortest path between P_{start} and P_{goal} while considering the allowable movement locations of the robot. The path should minimize the overall cost of ergonomic conditions along the trajectory, considering both the Euclidean distance and ergonomic condition goals. Mathematically, the optimization problem can be formulated as follows:

$$\begin{aligned} \text{Minimize:} \quad & w_d \cdot \sum_{i=1}^{n} D(P_i, P_{i+1}) + w_c \cdot \sum_{i=1}^{n} C(P_i) \\ \text{Subject to:} \quad & P_1 = P_{\text{start}} \\ & P_n = P_{\text{goal}} \\ & \forall i \in \{1, 2, \ldots, n-1\} : \quad P_i \text{ and } P_{i+1} \\ & \text{ are valid robot movement locations} \end{aligned} \tag{1}$$

Where P_i represents the pose of the tool at step i along the optimized path, and n is the total number of steps in the path. The objective function combines two terms: the weighted sum of Euclidean distances between consecutive points in the path and the weighted sum of ergonomic costs at each point. The weights w_d and w_c determine the relative importance of the Euclidean distance and ergonomic condition goals, respectively. The constraints ensure that the path starts from P_{start}, ends at P_{goal}, and the intermediate points P_i and P_{i+1} are valid robot movement locations within the allowable range of the robot.

By solving this optimization problem, an optimized and shortest path can be obtained, guiding the robot's movement to facilitate the exchange of the workpiece to promote ergonomic posture for the human operator while considering both the Euclidean distance and ergonomic condition goals.

Methodology

Human-Robot Shared Workspace Modelling

Within a shared workspace, cobots can manipulate the positioning of essential tools to ensure that a human partner can ergonomically reach them. The permissible locations for tool relocation in this shared workspace are determined by the feasible areas within the robot's workspace. To address this, a geometric model of the robot's workspace is established, considering the allowable locations for the robot. The feasibility of humans reaching those points is also investigated to ensure human capabilities compatibility. Consequently, this analysis determines the potential positions for tool relocation by aggregating the identified feasible points.

Robot Workspace Geometrical modeling of a robot's workspace involves determining the spatial boundaries within which the robot can operate. This modeling typically considers the allowable range of motion of the robot's joints and end-effector and any physical limitations or constraints imposed by its design. One commonly used approach is to approximate the robot's reachable workspace as an ellipsoid as in Figure 3. The ellipsoid represents a three-dimensional geometric shape that captures the feasible positions the robot can achieve based on its joint limitations. This ellipsoid represents the instantaneously reachable positions from a given point. However, it is essential to note that not all points within the ellipsoid are reachable for the robot. The joint limitations restrict certain areas of the ellipsoid, resulting in unreachable regions. For example, a robot with limited joint angles or physical constraints might be unable to reach certain extreme positions or orientations within the ellipsoid. The mathematical formulation for the ellipsoid of the Franka robot used in this research is given in Equation 2:

$$\begin{aligned} &\frac{(x-x_0)^2}{a^2} + \frac{(y-y_0)^2}{b^2} + \frac{(z-z_0)^2}{c^2} = \\ &\quad \frac{(x)^2}{0.855^2} + \frac{(y)^2}{0.855^2} + \frac{(z-0.333)^2}{0.857^2} = 1 \end{aligned} \tag{2}$$

In this equation, (x, y, z) represent the Cartesian coordinates of a point on the ellipsoid. At the same time, (x_0, y_0, z_0) denotes the coordinates of the ellipsoid's center. In this case, they are all set to (0,0,0.333). The parameters a, b, and c represent the lengths of the semi-axes along the x, y, and z directions, respectively, which are determined by the robot's physical specifications.

By fixing the position of the human relative to the robot as in Figure 1, a specific scenario can be examined, such as a drilling task performed by the human. In this context, one cross-section of the ellipsoid representing the robot's workspace can be selected as a 2D plane parallel to both the human and the robot as in Figure 3. This cross-sectional plane captures the feasible positions and orientations of the robot's end-effector for the drilling task, and the equation for this final shared workspace can be represented as an ellipse:

$$\left(\frac{x^2}{(0.855^2 \cdot (1 - \frac{0.33^2}{0.855^2}))} + \frac{(z-0.333)^2}{(0.857^2 \cdot (1 - \frac{0.33^2}{0.855^2}))} = 1 \tag{3}$$

Within this 2D plane, the robot's reachable workspace is represented by an ellipse. The major and minor axes of the ellipse correspond to the maximum distances the robot can reach in the plane in each direction, respectively. The shape and size of the ellipse depend on factors such as the robot's joint limitations, tool length, and any physical obstacles present in the workspace.

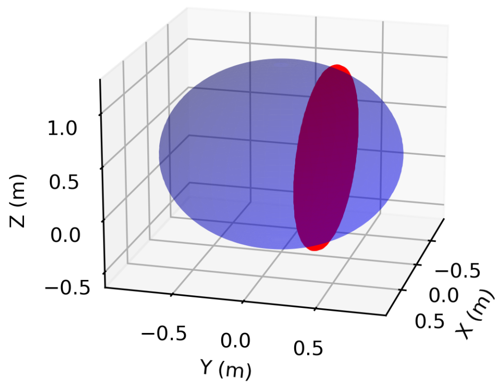

Figure 3. The robot's reachable workspace is shown as an ellipsoid (blue area) and a 2D highlighted ellipse cross-section(red area). This 2D ellipse or red shape is the modeled shared workspace in this research.

Human-Robot Workspace Cell-Decomposition Cell decomposition is a method for dividing a given space into smaller regions, known as cells, to aid analysis and planning. When dealing with a 2D ellipse representing a robot's workspace, cell decomposition can be employed to determine potential positions for relocating a workpiece. The procedure involves discretizing the ellipse into a grid or mesh composed of smaller cells, where each cell represents a viable position within the robot's reachable workspace for relocating the workpiece. The size of the cells can be adjusted based on the desired level of detail or the specific task requirements. Decomposing the 2D ellipse into cells depicts feasible positions, providing valuable information for planning the robot's motions and executing the task at hand.

Human Posture Estimation

An inverse kinematic approach makes it possible to estimate a person's posture while standing in various body configurations due to handling a tool in different locations. This methodology involves analyzing the human body's joint angles and segment positions, enabling the creation of an estimation model that considers the relationships between these variables. By considering factors such as tool position and grip, the inverse kinematic model can estimate the precise body posture that an individual will likely adopt while reaching the tool at a specific point in the shared workspace.

3D human body reconstruction with inverse kinematics typically involves capturing motion data using sensors or cameras, processing this data to create a 3D body model, and then applying inverse kinematics algorithms to animate the model. The algorithms adjust the positions of the bones in the model based on the body's desired movement and the model's constraints, such as joint angles and range of motion. One of the benefits of using inverse kinematics for 3D human body reconstruction is that it allows for natural and realistic movements of the body.

FABRIK is an algorithm widely used to solve inverse kinematics problems in 3D animation and robotics. It operates by iterative adjusting the positions of interconnected bones in a hierarchical structure until they reach the desired end position. The algorithm employs a "forward and backward reaching" approach, alternating between two stages: the forward stage, where the end effector position is set, and the backward stage, where the base bone position is adjusted to its initial pose. FABRIK calculates the distance between the current and desired end effector positions in each iteration and distributes the error among the chain's bones based on their relative distances. This process continues until the error falls below a certain threshold (Aristidou and Lasenby 2011).

FABRIK has an advantage over other inverse kinematics algorithms. It can produce natural-looking and smooth motion, even for complex structures with multiple degrees of freedom, by allowing bones to deform and bend realistically while preserving the model's overall structure. FABRIK is also computationally efficient, making it well-suited for real-time gaming and virtual reality applications. In the context of 3D human reconstruction, FABRIK can generate precise and realistic models of human behavior and motion by analyzing motion capture data and translating it into a 3D animated model (Aristidou et al. 2018).

To use FABRIK for human body reconstruction*, it should be noted that the human body consists of consecutive kinematic chains chained together. 3D human body reconstruction modeling begins by establishing a hierarchical skeleton structure representing the body. The joint positions are initially set based on available data, and target positions are specified. Forward reaching is then performed to update the joint positions towards the end effector. Subsequently, backward reaching is conducted to adjust the joint positions towards the root joint while maintaining bone lengths and structure. These forward and backward-reaching steps are repeated until convergence is achieved. The reconstructed 3D model is visualized using the updated joint positions, and refinement techniques can be considered to enhance accuracy. This entire process enables the reconstruction and modeling of the 3D human body using FABRIK and the target positions provided while adhering to the kinematic constraints of the skeleton structure. Figure 4 shows the FABRIK algorithm simulating the human body while reaching a target in his hand.

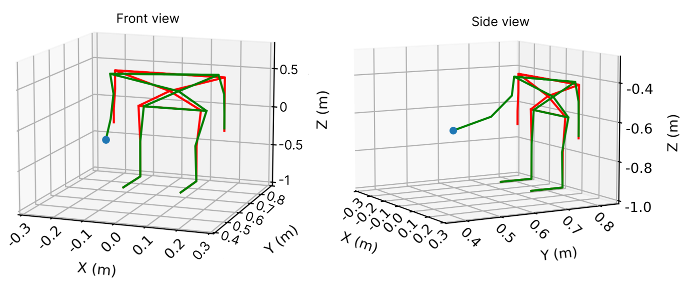

Figure 4. The human body has been reconstructed using FABRIK, with the red curve representing the initial neutral pose and the green curve depicting the individual's posture as they reach the point with their hand.

Postural Ergonomic Evaluation

*https://github.com/Atiehmerikh/FABRIK_Full_Body

Human posture ergonomic assessment is a crucial aspect of ensuring the well-being and comfort of individuals in various settings, especially in workplaces and industrial environments. This process involves evaluating the alignment and positioning of the human body during tasks to minimize the risk of musculoskeletal disorders (MSDs) and discomfort. Increased interest in automatic postural assessment, facilitated by cost-effective human tracking systems, has gained momentum. Although the REBA technique was initially designed for manual observations, its ability to handle static and dynamic postures and reliance on quantitative metrics renders it suitable for automated assessment. This method quantifies ergonomic preferences using a table-based approach. Initially, individual body parts (e.g., trunk, neck, upper arms) are assigned scores based on their angles during the assessment. Subsequently, an overall score is computed using reference tables that consider the relative importance of each body segment. For instance, a score of 3 for the trunk carries a higher risk weight than the same score for the upper arm. Finally, its output is a REBA score between 1 and 15, representing the level of MSD risk associated with the considered task. A higher score indicates a greater risk of MSDs.

The utilization of REBA score measurements in human-robot collaboration scenarios has a rich history. Collaborative robots play a vital role in improving the ergonomics of industrial workers by suggesting safer postures, thus reducing musculoskeletal risks. The NeuroErgo (Nejadasl et al. 2022) model, a deep neural network, surpasses traditional tabular ergonomic assessment methods, delivering more precise approximations. This facilitates the establishment of ergonomic postures during industrial tasks, ultimately enhancing worker well-being. Another approach involves using personalized kinematic modeling to evaluate worker postures, with robots optimizing tasks to ensure safer positions. Including a differentiable variable, dREBA (Busch et al. 2017), plays a pivotal role in solving optimization problems for ergonomic posture recommendations, further contributing to enhancing ergonomics in industrial environments. Leveraging the autonomy offered by REBA, we can seamlessly integrate it into the proposed ergonomic improvement methodology as the ergonomic assessment method.

Ergonomic Improvement

Ergonomic Path: In a 2D ellipse (Figure 3) that is decomposed into cells, each point can be assigned a number that represents the ergonomic score of the human while reaching that point (Figure 6). This score was calculated using the REBA score measurement technique. When designing a path for a human to move from an initial configuration to a final configuration, the goal is to find the most ergonomic path that minimizes the sum of the REBA scores along the path. Considering each point on the mesh grid has one REBA score, an optimization problem can be formulated to determine the path that results in the lowest overall ergonomic strain for humans. This can lead to a safer and more comfortable path for the human, reducing the risk of injury and improving overall efficiency.

Path Planning: The A* algorithm is a popular path-finding algorithm (Ju et al. 2020) that can find the most efficient path between an initial and final configuration while minimizing the ergonomic strain. To use the A* algorithm for this problem, the steps are explained in Algorithm 1. The steps are detailed in what follows:

The algorithm starts with q_i and q_f denoting the initial and final configurations, respectively, and G denotes the mesh grid with REBA scores.

Step 1: Initialize a priority queue labeled as Q, which will be used to manage and explore different configurations along the path. - Add the initial configuration, q_i, to the priority queue. This configuration represents the starting point of the path.

Step 2: Set the current cost of the path from the initial configuration to 0, represented by $g(q_i) = 0$. This keeps track of the accumulated cost to reach the current configuration.

Step 3: Calculate the heuristic estimate of the remaining cost to reach the final configuration from the initial configuration, $h(q_i)$. The heuristic provides a rough estimate of the cost needed to reach the goal. It guides the search toward the goal configuration. In Equation 4 to 6, different choices of heuristics are examined for an experiment to choose the most suitable one for the intended application.

Step 4: This is the core of the A* algorithm and involves an iterative loop until a path to the goal is found or determined to be unreachable.

Step 4a: Remove the configuration q_c with the lowest total cost, $f(q_c) = g(q_c) + h(q_c)$, from the priority queue. This configuration represents the most promising next step in the path.

Step 4b: Check if the selected configuration, q_c, is the final configuration, q_f. If it is, terminate the algorithm, and the initial to final configuration path is considered complete.

Step 4c: For each neighboring configuration, q_n, of the currently selected configuration, q_c, on the mesh grid, perform the following sub-steps:

- Calculate the cost of the path from q_c to q_n by adding the ergonomic score of q_n to the current cost of the path, $g(q_c) + e(q_n)$. This considers the cost of ergonomic optimization when transitioning from one configuration to another.

- If q_n is not in the priority queue Q, add it to the queue with the calculated cost and heuristic estimate, $g(q_n) = g(q_c) + e(q_n)$ and $h(q_n)$. This means q_n is a potential step in the path.

- If q_n is already in the priority queue,Q, and the newly calculated cost is lower than its current cost, update its cost and heuristic estimate in the priority queue, $g(q_n)$. This keeps track of the most cost-effective path to reach q_n.

Step 4d: If, after exploring all neighboring configurations, the final configuration q_f has not been reached, continue with the loop.

The algorithm repeats the steps of selecting the next configuration with the lowest cost, exploring neighboring configurations, and updating costs until it either successfully reaches the goal configuration q_f or determines that there is no valid path to q_f.

Step 5: First, a heuristic function is assigned to estimate the remaining distance to the final configuration from each point on the grid. This heuristic function can consider factors such as the Euclidean distance between the current point and the final configuration and the ergonomic score of the final configuration.

The algorithm combines the principles of the A* search algorithm with ergonomic considerations to find the most efficient path from the initial to the final configuration while minimizing ergonomic strain. It prioritizes configurations based on their total cost, including the cost of the path traveled so far and an estimate of the remaining cost. This way, it intelligently explores different paths and updates the path cost as it proceeds toward the goal. Consequently, the path produced by the A* algorithm offers the most efficient route between the initial and final configurations while minimizing ergonomic strain. Combining the A* algorithm with ergonomic scoring methods like REBA allows us to design paths prioritizing human safety and comfort while optimizing overall efficiency.

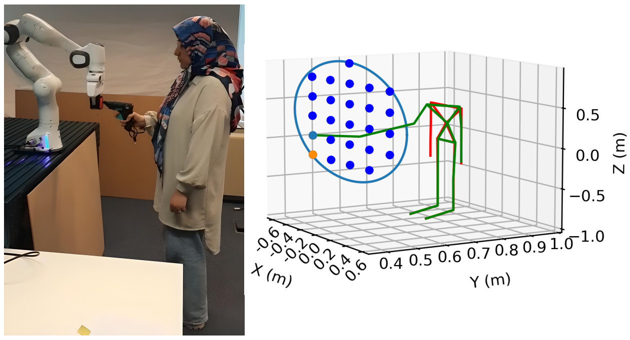

Figure 5. Illustration of a collaborative workspace where a human and robot coexist. The ellipsoidal workspace, decomposed into cells, captures the human's posture and the robot's constrained movements. This visual showcases the practical application of the proposed methodology in evaluating ergonomic considerations within shared workspace dynamics. The red curve is the initial posture of human and the green curve is the posture while reaching the point on the ellipse.

Results and Validation

This section offers an assessment of the effectiveness of our methodology in two pivotal dimensions. Firstly, we scrutinize the path-finding process within the shared workspace by comparing two established methods with different heuristics. This analysis aims to identify the most suitable approach for human-robot collaboration, prioritizing ergonomics. Secondly, we apply our methodology to real-world related tasks, assessing its impact on reducing ergonomic strain. The subsections, "Part 1. Comparison of Path Planners" and "Part 2. Evaluating Path Planner's Impact on Participants" offer detailed setups, prerequisites, and results, providing insights into the performance of path-finding methods and the observed changes in ergonomic conditions during industrial tasks.

Part 1. Comparison of Path Planners

Experimental Setup: The experimental setup, depicted in figure 5, portrays a human standing in proximity to a collaborative robot, presenting a scenario that embodies the principles outlined in the proposed methodology of this paper. In the shared workspace, symbolized by the ellipsoidal region, the robot is engaged in its tasks. The ellipsoid is meticulously decomposed into cells, each representing a distinct portion of the workspace. Notably, the human and the robot coexist within this shared space, highlighting the collaborative nature of their interactions. The elements of interest within this setup include the human's posture and position, crucial aspects for ergonomic assessment using the proposed methodology. The robot's movements are constrained by the delineated ellipsoid, emphasizing the significance of understanding the accessible regions and limitations of both human and robot within the shared workspace.

- **Collaborative Robot (Technical Setup):** The evaluation setup consists of the FRANKA Emika Panda robot, used in both simulation and real-world scenarios. In the actual setup, the robot is placed on a table with a height of 845 mm while a person's joints are tracked with the Microsoft Kinect V2 device as a motion capture sensor that stands in front of it. The implemented algorithm is in Python, incorporating motion planning with MoveIt and utilizing ROS as the middleware for seamless communication and coordination. This setup enables comprehensive evaluation of human-robot interaction, motion tracking, motion planning, and system performance in simulated and real-world environments.
- **Shared Workspace:** In the context of the Panda robot's workspace modeling, it is represented as an ellipsoid with a formulation described in Equation 2. Following the decomposition of the ellipse into cells, it's crucial to acknowledge that while the entire shared workspace is theoretically accessible for a human (assuming an obstacle-free environment and human limitations defining the workspace's border), the same is not true for the robot. Due to constraints related to the robot's joint movements, certain points within the workspace become inaccessible for the robot (Trabelsi et al. 2021). These unreachable areas are visually identified by absent or differently marked cells, as illustrated by the blue dots in Figure 6. Overall, this shared workspace, shared by human and robot, is conceptualized as a weighted graph where nodes represent human postures with corresponding REBA values while reaching.

Experimental Design: The path-finding algorithm is based on the A* search method described in the methodology section. In the following, this method is compared to the well-known Dijkstra algorithm Wang et al. (2011).

The goal is to find the most ergonomic path from the start node to the goal node. This path corresponds to the path for which the sum of the REBA scores associated with the nodes in the path is the lowest. The A* and Dijkstra's algorithms are thus the two possible options, as they both consider edge weights. With Dijkstra's algorithm, the lowest cost path from the start to the goal node based on edge weights (= ergonomic scores) is guaranteed to be found, with the condition that all edge weights are non-negative. The algorithm prioritizes nodes with lower cumulative scores. The A* algorithm uses the path's cost during its search and combines it with an estimated remaining cost defined by a heuristic function. Thanks to the heuristic, the algorithm explores the most

Algorithm 1 A* Path-finding Algorithm with Ergonomic Optimization

```
function AStarPathFinding(q_i, q_f, G)
    Q ← [q_i]                                              ▷ Priority queue
    g ← {q_i : 0}                                          ▷ Cost from the initial configuration
    h ← {q_i : HeuristicEstimate(q_i, q_f)}                ▷ Heuristic estimate
    while Q is not empty do
        q_c ← Min(Q, λx : g[x] + h[x])                     ▷ Get the lowest total cost configuration
        Remove(Q, q_c)
        if q_c = q_f then
            return ConstructPath(q_i, q_f)                 ▷ Terminate and return the path
        end if
        for q_n in NeighboringConfigurations(q_c, G) do
            cost_{q_n} ← g[q_c] + ErgonomicScore(q_n)
            if q_n not in Q then
                Append(Q, q_n)
                g(q_n) ← cost_{q_n}
                h[q_n] ← HeuristicEstimate(q_n, q_f)
            else if cost_{q_n} < g[q_n] then
                g(q_n) ← cost_{q_n}
            end if
        end for
    end while
    return None                                            ▷ Return failure if the final configuration is not reached
end function
```

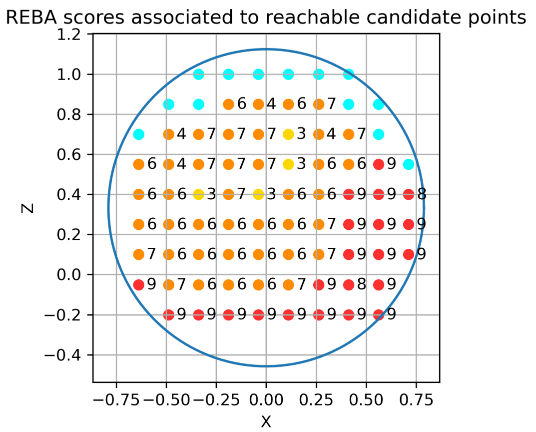

Figure 6. Figure illustrates the shared workspace of the Panda robot, represented as an ellipsoid and decomposed into cells. While the entire space is theoretically accessible for a human, certain points within the workspace become inaccessible for the robot, as denoted by blue dots. This shared workspace, common to humans and robots, is envisioned as a weighted graph.

promising paths first, which results in a more efficient exploration and could result in a faster convergence towards the goal node. Compared to the A* algorithm, Dijkstra's algorithm can be less efficient, especially in large graphs, as it explores all nodes without any additional guidance.

The A* algorithm is only optimal if the heuristic function is admissible and thus never overestimates the actual cost to reach the goal node (Zhang et al. 2021). For this reason, the performances of the A* algorithm when different heuristics are used, will be analyzed. It is necessary to determine the heuristic function to compare the results obtained using Dijkstra's algorithm and those obtained using the A* algorithm. Several heuristic functions are being taken into account for this purpose.

$$h_1(n) = |\text{ergonomic\_score}(\text{goal\_node}) - \text{ergonomic\_score}(n)| \tag{4}$$

$$\begin{aligned} h_2(n) =& w \cdot \text{distance}(\text{goal\_node}, n) \\ &+ (1-w) \cdot |(\text{ergonomic\_score}(\text{goal\_node}) \\ &- \text{ergonomic\_score}(n))| \end{aligned} \tag{5}$$

$$\begin{aligned} h_3(n) = \exp(&|\text{ergonomic\_score}(\text{goal\_node}) \\ &- \text{ergonomic\_score}(n)|) - 1 \end{aligned} \tag{6}$$

The heuristics (Equations 4, 5, 6) have been defined to achieve optimality. To address this, the path's score is calculated using different heuristics. In Equation 4, only the ergonomic score between the goal node and its neighboring nodes is considered. However, in Equation 5, the cost function incorporates the ergonomic score and the Euclidean distance. Lastly, Equation 6 explores the exponential function of the difference in ergonomic scores between nodes.

Results: The different implementations' performances are compared on three distinct graphs, depicted in Figure 7. These graphs correspond to scenarios where the human distances from the robot base are 0.8, 0.98, and 0.91 meters. Similarly, the distances of the modeled shared workspaces, each graph, from the robot, are 0.33, 0.7, and 0.5 meters. These distances represent the relative positioning of the ellipse from the robot. It is essential to note that the distance of the human to the robot is measured from the human's feet to the base of the robot. The robot's base point is considered a static reference point in this context. Finally, the number of nodes for each graph is 80, 32, and 65 respectively. These graphs and their respective characteristics provide a basis for evaluating and comparing the different implementations' performances.

Note that all nodes are connected in all directions to their adjacent nodes. The weights of the corresponding edges are defined as the ergonomic score of the destination nodes. So, for the edge going from node i to node j, the weight equals the REBA score of node j.

Considering every node once as a start node, a path is generated using the Dijkstra and A* algorithms using the different heuristics. The goal node is defined for each path as the node with the lowest ergonomic score. If multiple nodes satisfy this condition, the one closest to the start node is selected. The metric value obtained with Dijkstra is subtracted from that obtained with A* for each generated path and metric. This is repeated for every graph. The differences are then analyzed to determine which implementation to choose. In Figure 8, the box plots of the differences in run time between Dijkstra and A* are visualized.

Discussion of Part 1 Results: A negative sign in Figure 8 means that A* was faster than Dijkstra in generating the path and it is evident in most cases, that the A* algorithm is faster than Dijkstra, independently of the chosen heuristic. This is true for the three graphs. The spread of the data, represented by the distance between the lowest and highest horizontal lines, is the highest when h_1 is used in the A* algorithm and the weakest for h_3. This is also the case for the spread of the middle 50% of the data, which is indicated by the height of the box. Note that the spread decreases as the number of nodes in the graph decreases. The lower the spread, the more consistent the data. However, with h_1, more down run times are obtained for a higher percentage of the paths. Additionally, the number of times Dijkstra is faster than the A* algorithm is the lowest when h_1 is used.

The values clearly show that using h_1 consistently results in a faster run time on average compared to h_2 and h_3. Indeed, when h_1 is used in the A* algorithm, the average difference in run time with Dijkstra's algorithm is about two times higher (in absolute value) compared to when h_2 is used and even more compared to when h_3 is used.

Part 2. Evaluating Path Planner's Impact on Participants

Experimental Setup: To evaluate the adaptability of our algorithm in diverse human-robot collaboration scenarios, we employed an existing online dataset (Franco et al. 2017). This dataset, proposing an activity recognition approach using RGB-D cameras like the Kinect sensor, features 14 activities performed by 10 subjects aged 20 to 35. Subjects received minimal instructions to promote natural actions. The Microsoft Kinect V2 facilitated data acquisition, capturing position and orientation data for 25 joints. For testing, we applied the leave-one-out cross-validation method, recognized for providing unbiased estimates of model performance, particularly in cases with a small sample size (Rushing et al. 2015).

From the 14 activities in our investigation, we selected three specific tasks: retrieving an arbitrary object from a shelf, stacking several cubes on a table, and assembling a particular tool while seated behind a table. Participants performed these tasks without explicit instructions, allowing them to proceed at their comfortable pace, and ensuring a natural and unrestricted approach to their movements. The entire process, encompassing all three tasks, was meticulously recorded. With a specific sample size, the dataset was divided into 140 sequences, and each participant executed the activities twice, resulting in a total of 280 sequences. This approach facilitated a comprehensive examination of participant interactions with the tasks, capturing performance variations and contributing to a thorough analysis of human-robot collaboration scenarios.

Additionally, the dataset enabled the exploration of orientation and position data for 25 joints, of which 18 joints provided both position and orientation information. The Microsoft Kinect V2 recorded the position and orientation data for these 25 body joints at each time step. This dataset was instrumental in creating simulations for human-robot interaction scenarios, where our algorithm enhanced ergonomics. The algorithm's efficacy in improving human-robot collaboration across various real-world tasks was evaluated by assessing the final postures achieved. Independent variables included participant height, body type, and task type, while dependent variables comprised the final postures achieved.

Experimental Design The experiments were designed and executed to scrutinize the participants' final REBA values. This approach aimed to assess the algorithm's impact on the study outcomes, particularly focusing on the ergonomic status of participants throughout the collaborative tasks. Notably, the emphasis was placed on evaluating the quality of the final pose as an indirect reflection of the efficacy of the path planning module. To determine the effect and performance on different individuals, the path for each person was calculated using the A* algorithm, with h1 chosen as the preferred heuristic among various options discussed in Part 1 of the Results and Validation section. This investigation seeks to shed light on how the chosen path-planning strategy influences individual ergonomic outcomes, underscoring the significant role of the path-planning module in enhancing collaboration ergonomics.

The t-test emerges as a fitting statistical method for this study, aligning with its goals of evaluating the algorithm's impact on ergonomic outcomes in simulated human-robot collaboration scenarios (Ruxton 2006). The t-test is particularly suitable for assessing the effectiveness of the algorithm by comparing the REBA scores before and after its application, given the paired nature of these observations where each participant serves as their own control (Hedges and Hedberg 2007). This aligns with the assumptions of the t-test, which requires that the data points in the two groups (before and after applying the algorithm) are paired. Furthermore, the robustness of the t-test in handling small sample sizes is particularly relevant to the current study, as human-robot interaction experiments often involve a limited number of participants (Ruxton 2006). This characteristic of the t-test ensures that the statistical

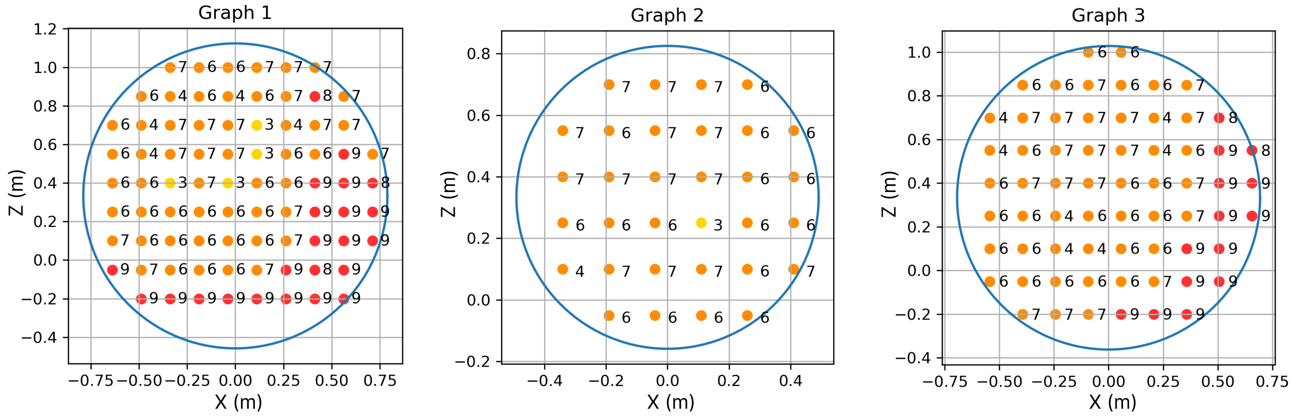

Figure 7. Three generated graphs for a single drilling example are used to compare the performances of the different implementations. Graph 1 with 80 nodes, Graph 2 with 32, and Graph 3 with 65 nodes. All the points in the workspace (= blue ellipse) represent the nodes in the graph. Every node is connected to its eight neighbors. The weight of an edge corresponds to the REBA score of the destination node.

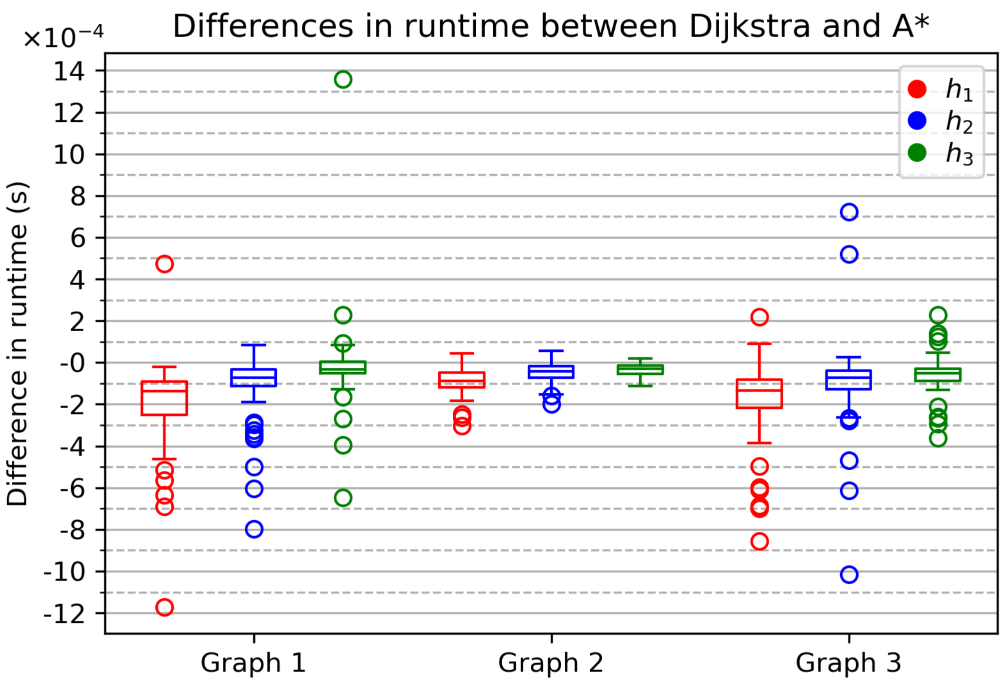

Figure 8. Box plots of the differences in run time between Dijkstra and A*. A negative sign means that A* is faster than Dijkstra in generating the path. The A* algorithm with h_1 shows the highest spread but is also the fastest.

analysis remains valid and reliable even with a small sample size, thereby enhancing the credibility of the study findings. The simplicity of the t-test also contributes to its suitability for this study, as it facilitates a clear interpretation of results (Keselman et al. 2004). This is essential in enhancing the transparency of the findings and making them accessible to a wider audience, including researchers, practitioners, and stakeholders in the field of human-robot interaction and ergonomics. With the t-test's appropriateness established for evaluating the algorithm's impact on ergonomic outcomes, the study formulates clear hypotheses to rigorously test the significance of differences between the initial and final REBA values.

- **Null Hypothesis (H0)**: No significant difference exists between the means of initial and final REBA values.
- **Alternative Hypothesis (Ha):** There is a significant difference between the means of initial and final REBA values.

Statistical Analysis: The statistical analysis, illustrated in Figure 9, provides robust evidence supporting the positive impact of algorithm implementation on ergonomic outcomes. The box plot on the left side of Figure 9 demonstrates a clear shift in the distribution of REBA values toward lower values after the algorithm intervention. Notably, the median REBA values exhibited a significant decrease, indicating improved ergonomic conditions. The reduction in the interquartile range (IQR) further supports these findings, suggesting a more consistent and reduced ergonomic strain for participants. Subsequent t-test results, with highly significant test statistics and extremely low p-values, consistently reject the null hypothesis. Specifically, the calculated test results (13.779, 12.209, and 12.043) for each task, along with the associated p-values (6.313×10^{-16}, 2.329×10^{-14}, and 3.464×10^{-14}), affirm the algorithm's substantial influence on reducing ergonomic strain during the tasks. These statistical outcomes confirm the research hypothesis, emphasizing the effectiveness of the algorithm in enhancing ergonomic conditions in simulated human-robot collaboration scenarios.

Conclusion and Future work

In conclusion, this paper presented a path-planning algorithm for guiding a robot to assist a human worker along the most ergonomic path while accomplishing an industrial task, like industrial painting or welding. It presented a novel approach to a path-planning algorithm explicitly tailored for human-robot collaboration. By addressing the unique challenges associated with human-robot collaboration, this novel algorithm advances robotic systems that can seamlessly work alongside humans, benefiting industries and society. The algorithm utilized Cartesian path planning with the cell decomposition method. The goal node with the lowest ergonomic score was determined using FABRIK and REBA. The A* algorithm, combined with a heuristic function based on the absolute difference in ergonomic scores, demonstrated superior performance in finding the most ergonomic path compared to Dijkstra's algorithm. The generated paths were successfully executed in simulations and on the physical FRANKA Emika panda robot. This research contributes to developing practical path-planning algorithms for optimizing ergonomics in human-robot collaboration scenarios.

In future works, several areas can be explored to enhance the findings further and contribute to optimizing ergonomics in human-robot collaboration. Firstly, a 3D model of the shared workspace can be considered. By incorporating three-dimensional representations of the workspace, a more comprehensive understanding of the spatial constraints and potential obstacles can be obtained, leading to improved path planning and ergonomic optimization. Another potential avenue for future research is investigating the effects of robot end effector velocity and acceleration during target relocation on the overall ergonomics. Understanding how different motion profiles of the robot's end effector impact the ergonomic aspects of the task can provide valuable insights for designing more ergonomic robot trajectories. Factors such as smoothness, jerk, and acceleration profiles can be examined to identify optimal movement patterns that minimize discomfort and strain on the human worker.

Furthermore, a noteworthy drawback of this approach is its exclusive dependence on kinematic measurements, which may not adequately capture the intricacies of modeling muscle forces – a key consideration in mitigating the risk of Musculoskeletal Disorders (MSDs), particularly in scenarios involving interactions with the environment. It is recommended to acknowledge this limitation in the study and propose that, in the future, more sophisticated measures for assessing MSD risk, capable of accounting for both muscle forces and environmental interactions, could potentially supplant the current use of the REBA score for more thorough and precise evaluations. Notably, the modular structure of this framework allows for the seamless integration of advanced ergonomic assessment methods as replacements for the existing ones.

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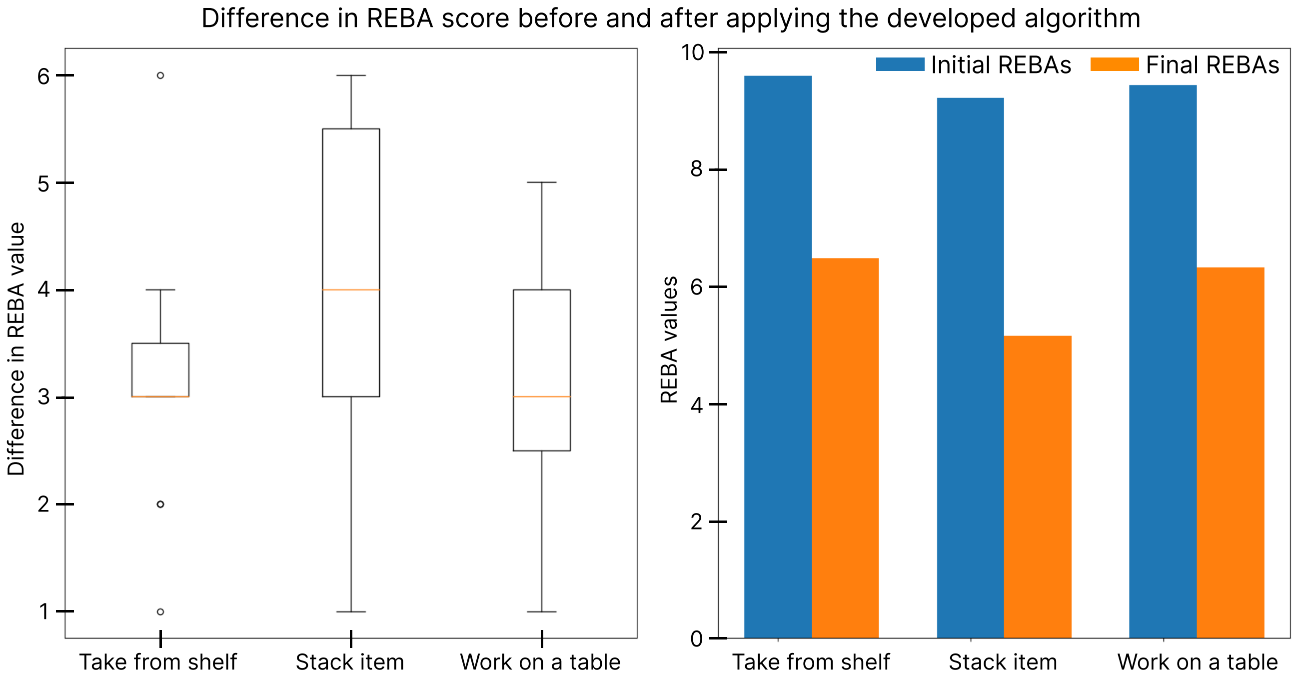

Figure 9. The box plot and bar plot for the 3 Experiments done on the human dataset (10 participants). The experiments are taking an arbitrary object from the shelf, stacking cubes, working behind a table while sitting, and assembling objects over there. The results show a significant reduction in the average score of REBA over the task after applying the algorithm.

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