A Human Digital Twin Approach for Fatigue-Aware Task Planning in Human-Robot Collaborative Assembly

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Abstract

Human-robot collaboration (HRC) has emerged as a pivotal paradigm in manufacturing, integrating the strengths of both human and robot capabilities. Neglecting human physical fatigue may adversely affect worker health and, in extreme cases, may lead to musculoskeletal disorders. However, human fatigue has rarely been considered for decision-making in HRC manufacturing systems. Integrating adaptive decision-making to optimise human fatigue in HRC manufacturing systems is crucial. Nonetheless, real-time perception and estimation of human fatigue and decision-making informed by human fatigue face considerable challenges. To address these challenges, this paper introduces a human digital twin method, a bidirectional communication system for physical fatigue assessment and reduction in human-robot collaborative assembly tasks. The methodology encompasses an IK-BiLSTM-AM-based surrogate model, which consists of inverse kinematics analysis (IK), bidirectional long short-term memory (BiLSTM), and attention mechanism (AM), for real-time muscle force estimation integrated with a muscle force-fatigue model for muscle fatigue assessment. An And-Or graph and optimisation model-based HRC task planner is also developed to alleviate physical fatigue via task allocation. The efficacy of this approach has been validated through proof-of-concept assembly experiments involving multiple subjects. The results show that the IK-BiLSTM-AM model achieves a minimum of 8% greater accuracy in muscle force estimation than the baseline methods. The 12-subject assessment results indicate that the task planner effectively reduces the physical fatigue of workers while performing collaborative assembly tasks.
Keywords: physical fatigue, human digital twin, human-robot collaboration, human-centric manufacturing, ergonomics.

1. Introduction

Human-Robot Collaboration (HRC) has emerged as a vital manufacturing paradigm that integrates the versatility of human workers with the strength and consistency offered by robots (Wang et al., 2020). This paradigm provides a cooperative environment where diverse agents collaboratively execute manufacturing tasks within a shared workspace. On the other hand, research on digital twins, especially human digital twins (Peruzzini et al., 2023), has accelerated the development of the HRC by creating virtual counterparts of physical models in recent years. Numerous research efforts have been channelling digital twin technologies toward creating ergonomic HRC manufacturing environments (Bilberg and Malik, 2019).

In assembly tasks, manual labour inevitably leads to worker fatigue. In severe cases, human fatigue can lead to musculoskeletal disorders, detrimentally impacting the well-being of individuals. However, incorporating the factors of human fatigue into HRC assembly lines presents several challenges. One primary challenge is the absence of a real-time muscle-specific approach for assessing human physical fatigue levels. This is essential for mitigating the negative impact caused by human fatigue (Wang et al., 2022). For instance, subjective assessment methodologies, such as the Borg RPE scale (Williams, 2017), may result in imprecise evaluations and potentially disrupt standard workflows. Ergonomic approaches, such as Rapid Upper Limb Assessment (McAtamney and Corlett, 2004), struggle to accurately reflect individual differences in human physical fatigue. In addition, musculoskeletal model-based methods, such as human activity simulation based on OpenSim (Dembia et al., 2020), present a promising approach for muscle fatigue assessment. However, this method has a high computational burden and thus does not meet the needs of real-time muscle fatigue assessment.

On the other hand, fatigue-aware decision-making for physical fatigue reduction in HRC is limited in the literature. Some studies have focused on developing HRC scheduling algorithms to optimise worker fatigue in manufacturing (Yao et al., 2023; Zhang et al., 2022). However, the validation of these methods has been limited to simulation levels, lacking support from practical application results. Furthermore, other studies have focused on role allocation (Merlo et al., 2023; Messeri et al., 2022) and co-manipulation (Peternel et al., 2018a) during the HRC process aimed at alleviating human fatigue. However, their research focused only on single movement and did not address fatigue optimisation throughout the entire assembly process, failing to meet the complexity and uncertainty requirements inherent in product assembly tasks.

The above analysis reveals a critical gap: the absence of a real-time tool for assessing worker fatigue and a task planning method in HRC for human fatigue alleviation. To address the aforementioned research gaps, this paper proposes a novel human digital twin-based method for real-time muscle-level physical fatigue assessment and fatigue reduction among manual workers in HRC assemblies. A surrogate model, namely, IK-BiLSTM-AM, is introduced to estimate the muscle force caused by human movements. This model is integrated with a muscle force-fatigue model to enable analysis of muscle fatigue. Furthermore, an And-Or graph and single-objective optimisation model-based HRC task planner are presented, aimed at reducing physical fatigue through dynamic task allocation. The human digital twin receives movement data from the human operator for fatigue estimation and returns allocation plans to alleviate worker fatigue, forming a bidirectional closed-loop communication system. The effectiveness and accuracy of this approach were rigorously validated in a proof-of-concept assembly experiment, with a particular focus on the surrogate model's accuracy and the task planner's efficiency in alleviating physical fatigue.

The contributions of this paper are summarised as follows:

(1) A surrogate model, named IK-BiLSTM-AM, is proposed for real-time muscle force estimation for human movements in HRC tasks.
(2) A novel human digital twin-based method is proposed for real-time human physical fatigue assessment in HRC assembly tasks.
(3) A fatigue-aware task planner is introduced based on an And-Or graph and optimisation model, which is utilised to distribute tasks between humans and robots to minimise human physical fatigue in HRC.
(4) A real-world HRC assembly experiment involving multiple subjects is designed to validate the efficacy of the proposed surrogate model and the task planner.

2. Literature review

2.1. Human physical fatigue assessment methods

Manual workers who engage in tasks with high physical demands, especially those in assembly line work, face a high risk of developing musculoskeletal disorders (Onaji et al., 2022). This heightened risk is caused by prolonged and repetitive tasks, particularly those involving repetitive hand or arm movements. Implementing effective fatigue management strategies in the workplace is a practical approach to mitigate these risks. Various techniques have been suggested for measuring physical fatigue, encompassing both subjective self-reports and objective measurements. However, these existing methods fall short of providing continuous, automatic, and precise assessments of physical fatigue.

Subjective fatigue assessment methods rely on workers self-reporting their physical fatigue levels based on personal perceptions during work. Notable examples include the Borg RPE scale and the Borg CR10 scale (Williams, 2017). However, these subjective methods present certain limitations: (1) the accuracy of the assessment results can be questionable, and (2) conducting these assessments may disrupt regular work activities.

On the other hand, there are three main categories of objective methods for assessing fatigue: physiological indicators, ergonomic methods, and biomechanical methods. Given that human physical activity is fundamentally a physiological process, fatigue can be evaluated through physiological signals, such as heart rate (Argyle et al., 2021) and surface electromyography (Wang et al., 2021). Nevertheless, both methodologies are influenced by individual physiological and biochemical factors, as well as external environmental factors.

Ergonomic approaches can evaluate worker fatigue to facilitate comfortable engagement in repetitive motions while minimising injury risks. Notable examples of such methods include the Rapid Upper Limb Assessment and Rapid Entire Body Assessment (McAtamney and Corlett, 2004). However, a primary shortcoming of ergonomic methods lies in their limited accuracy in assessing human body fatigue. These approaches often overlook differences in human anthropometry, which can significantly influence the precision of the assessment results. Additionally, they tend to rely on simplified representations of human anatomy for fatigue evaluation, potentially failing to accurately reflect the variability inherent in human behaviours (Plus, 2018). As a result, assessments derived from different ergonomic methods may yield inconsistent results.

Musculoskeletal models represent digital twins of the human body, comprising computational representations of bodily structures and functions (van der Have et al., 2023). They are increasingly used for assessing biomechanical fatigue by simulating the dynamics of bones, joints, and muscles during physical activities. These simulators, such as OpenSim (Dembia et al., 2020), offer valuable insights into the physical strains that contribute to the development of physical fatigue. However, the complexity inherent in musculoskeletal models requires multiple data sources, such as human body movement and contact forces. This requirement can lead to extensive preparation times, even for experts in the field. Furthermore, the computational demands for analysing musculoskeletal models are significant (Aftabi et al., 2021), posing a challenge for their real-time application in various scenarios, including HRC. Therefore, reducing the complexities associated with these models and enhancing their practical utility are critical objectives, and they form the core focus of this study.

2.2. Fatigue mitigation aimed at HRC task planning

In the realm of HRC in manufacturing, recent years have witnessed a growing body of research on the application of physical fatigue perception. Notably, many studies have focused on the development of scheduling algorithms designed to optimise worker fatigue in HRC. To address the adverse effects of fatigue on worker efficiency, Kai et al. introduced a discrete bees algorithm for sequencing planning aimed at minimising the time required for disassembly tasks (Li et al., 2019). Ming et al. incorporated rest periods into job cycles to facilitate recovery from accumulated fatigue. Subsequently, they introduced a chemical reaction optimisation approach for task scheduling, aiming to balance cycle time with human fatigue management (Zhang et al., 2022). Given the significant demand for cognitive abilities in HRC tasks, Yao et al. developed an approach that merges a multimodal-based mental fatigue perception model with a task reallocation framework. This integration allows for dynamic adjustments to the work plan in response to the varying mental states of the worker (Yao et al., 2023). Despite these advancements, most of these methodologies have undergone validation at the simulation level, with a notable deficit in evidence from real-world applications.

Additionally, some studies have focused on role allocation and co-manipulation during the HRC process. Elena et al. proposed a risk indicator for tasks based on historical actions and the current physical configuration of the body. This indicator can personalise the identification of high-risk tasks for subjects, thereby preventing their allocation to human operators (Merlo et al., 2023). Luka et al. developed a method for detecting muscle group fatigue based on musculoskeletal models. This approach facilitates rapid robot responses in co-manipulation tasks, directing force distribution to muscle groups of the worker that are less fatigued (Peternel et al., 2018a). Driven by 3D vision-driven musculoskeletal models, Costanza et al. (Messeri et al., 2022) introduced a task allocation strategy intended to mitigate human fatigue. The aforementioned methods predominantly rely on camera-based vision techniques. In complex manufacturing environments, such as workshops, vision-based methods are susceptible to occlusion and can suffer from issues related to accuracy.

In addition, these works focused only on the aspect of movements and lacked effective integration into actual assembly processes, thereby failing to address the complexities and uncertainties of assembly operations.

To overcome the identified limitations, this study presents a methodology with inertial measurement unit (IMU) data as input, which has high accuracy. We utilise an And-Or graph to depict the process of assembly tasks, decomposing hierarchically the complex process into task units. By integrating these components, our research introduces an innovative dynamic role allocation strategy specifically designed to reduce physical fatigue in assembly tasks.

3. Methodology

This research presents a novel method for reducing human physical fatigue, leveraging a continuous, real-time physical fatigue assessment approach and fatigue-aware task planner for assembly tasks. The proposed workflow is depicted in Figure 1. Communication between the human operator and the digital twin model is bidirectional. The motion data of the human operator is collected using IMUs for IK-BiLSTM-AM training and human muscle fatigue assessment. In return, the empirical fatigue data assessed by the surrogate model informs the task planner, optimising the task plan that guides the agents for the assembly task. The functionality of the human digital twin is built upon a four-step process. The initial step involves establishing a personalised digital twin human model by scaling the universal musculoskeletal model, informed by movement data obtained from IMUs. Subsequently, our proposed IK-BiLSTM-AM network for biomechanical analysis, enabled by a deep neural network, is employed to estimate human muscle forces with IMU data as input. Following this, the paper introduces a dynamic task planner that integrates an And-Or graph with an optimisation model, generating optimised task allocation solutions in real-time. The final section demonstrates the practical application of this method, featuring a graphical user interface (GUI) tailored for the task planner in HRC assembly tasks.

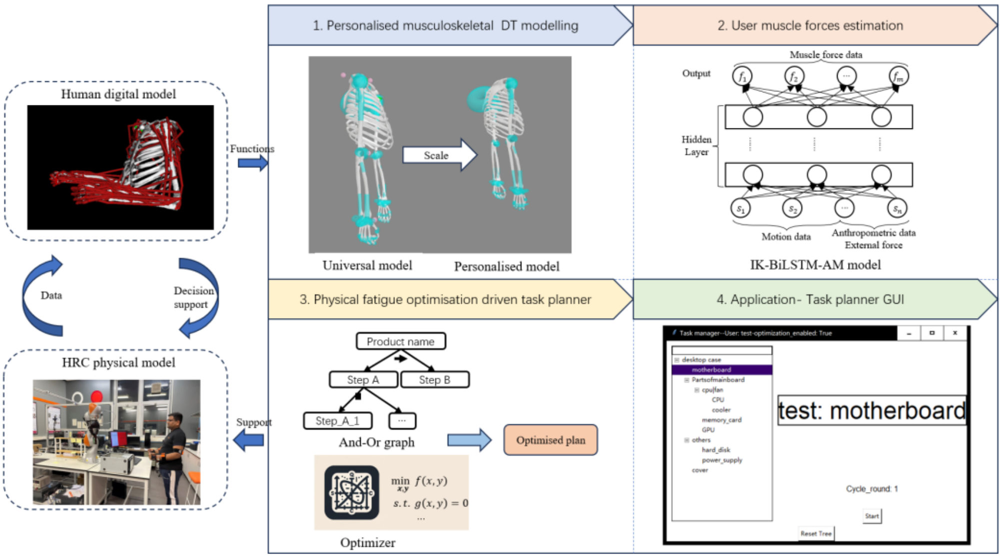

Figure 1. The workflow of the proposed human digital twin model for reducing human physical fatigue. Step 1: scale the universal upper limb model based on the anthropometric information to obtain a personalised model (Section 3.1). Step 2: an IK-BiLSTM-AM model is proposed for the muscle forces estimation (Section 3.2). Step 3: An And-Or graph-based optimiser is introduced to generate the HRC assembly allocation plan (Section 3.4). Step 4: A task planner GUI is built for visual interaction in HRC application (Section 4).

3.1. Musculoskeletal digital twin modelling

The computational musculoskeletal simulation provides an effective digital twin solution for evaluating muscle contributions to human motions. A musculoskeletal model, specifically the bimanual upper arm model (McFarland et al., 2019) was proposed to understand the movements of the human upper limbs. This model allows for the simulation of bones, joints, and muscles involved in human motions, incorporating inputs of human motion data and external forces. The kinematic foundation of the model encompasses several key components: the glenohumeral joint, elbow, forearm, wrist, thumb, and index finger. Overall, the model has a total of 28 degrees of freedom and is designed symmetrically. Based on the bimanual upper arm model, a musculoskeletal digital twin method for human fatigue alleviation is proposed in this work. Figure 2 depicts the flowchart of the proposed digital twin framework, which consists of three phases: preparation phase, training phase and execution phase.

During the preparation phase, the bimanual upper arm model is scaled to align with the manually measured dimensions of the human operator's body segments, generating a personalised model. The scaling is to ensure analysis accuracy and individual relevance. The musculoskeletal digital twin model is driven by precise human movement data. To accurately record upper limb movements, we use the Xsens Awinda IMUs due to their high accuracy, achieving 1 degree root mean square (RMS) errors in static conditions and 1.5 degrees in dynamic conditions (Myn et al., 2015). Research (Schepers et al., 2018) shows that RMS differences for the dominant joint angles using the Xsens system are less than 5 degrees, which are considered acceptable in most clinical applications (Di Raimondo et al., 2022). In our study, nine IMUs are strategically attached to specific body parts of each participant: the chest, scapula, upper arm, forearm, and hand, as shown in Figure 3. Each IMU aligns with a corresponding body segment to ensure tracking and measurement of movements.

Since existing methods fail to meet the requirements for real-time applications, we have developed a surrogate model, IK-BiLSTM-AM, for muscle force estimation in HRC, as detailed in Section 3.2. Consequently, the training phase outlined in the flowchart involves training the proposed network using a dataset collected from biomechanical simulation, the OpenSim, which uses real human movement data collected in this work. The execution phase demonstrates how the trained IK-BiLSTM-AM network is employed for muscle force prediction, the force-fatigue model is utilised for muscle fatigue estimation (described in Section 3.3), and the task planner is applied for assembly task planning (outlined in Section 3.4). The software and the hardware used in this study are shown in Table 1.

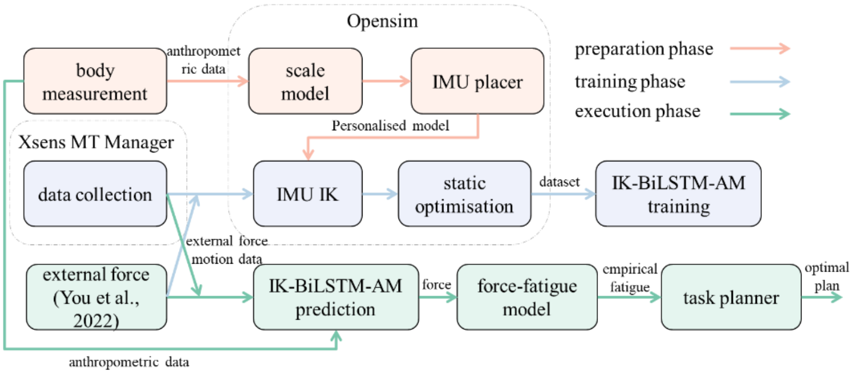

Figure 2. The flowchart of the proposed digital twin method for muscle fatigue alleviation.

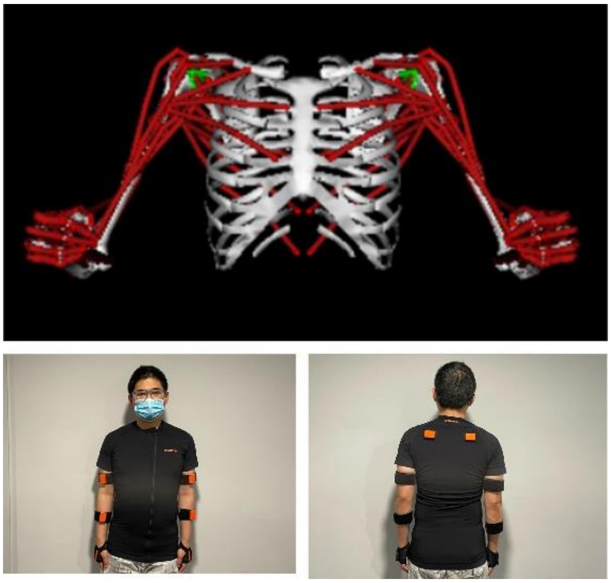

Figure 3. The upper limb musculoskeletal model and a participant are equipped with Xsens IMU sensors for demonstration.

Table 1. The software and hardware used in the human digital twin model

Hardware	Software
Xsens IMU sensors	Xsens MT manager (Human movement data collection)
Kuka iiwa LBR robot	OpenSim (IK-BiLSTM-AM training data preparation)
Robotiq 3-Finger Robot Gripper	Pytorch (IK-BiLSTM-AM modelling)
	Robot Operating System (Robot control)
	Gurobi (Task planner optimiser)

3.2. Muscle force estimation

While biomechanical analysis is effective in estimating human muscle forces, its computational complexity leads to long processing times to obtain an optimal estimation of muscle forces. To address this challenge, adopting advanced deep learning techniques is a viable alternative to traditional biomechanical computations. Gaussian Process Regression can be used for muscle force estimation. However, it is limited when dealing with the non-linear and non-stationary nature of muscle force estimation (Rogers et al., 2020). Long short-term memory (LSTM) networks are widely deployed for processing sequential historical data; however, such networks are generally less efficient at capturing future contextual information (Van Houdt et al., 2020). This limitation hinders their ability to extract specific features within the movement data in this work. Moreover, the intricate interrelations and varying significance of motion data features pose additional challenges for LSTMs, affecting the precision of muscle force predictions.

To surmount these obstacles, this paper proposes a novel network structure named IK-BiLSTM-AM, which integrates IK analysis, BiLSTM, and an AM. The architecture of this network is depicted in Figure 4. In this framework, IK is employed to transform sensor signals into joint rotation and translation data of the human body. The transformation allows the BiLSTM to better capture and understand the contextual information in human motion data, extracting relevant movement features. Concurrently, the AM assesses the importance of these features and focuses on the most relevant feature within the sequence data, thereby refining the correlation between movement data and muscle forces. The IK-BiLSTM-AM structure combines the interpretability of IK with the sequential learning capabilities of BiLSTM and the selective focus of the attention mechanism to enhance the accuracy and efficiency of muscle force estimation in real-time applications.

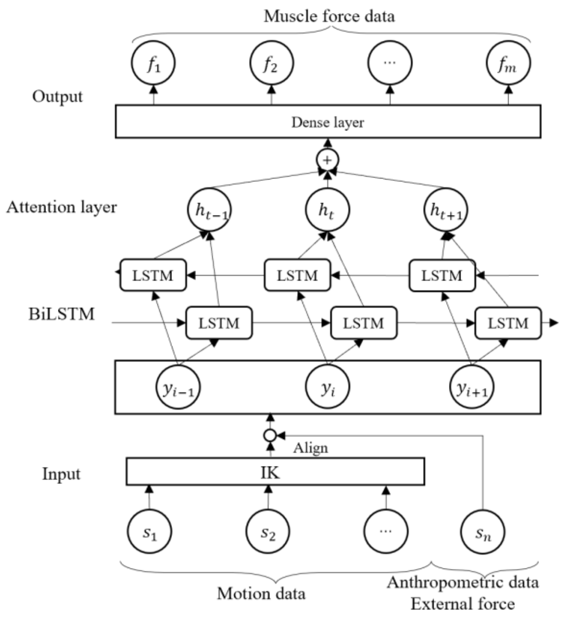

Figure 4. The structure of the proposed IK-BiLSTM-AM method. Initially, human motion data is processed through the IK layer, where it is transformed into the joint rotation and translation data of the human body, aligned with anthropometric measurements and muscle force data. Following this, the data features are extracted using the BiLSTM layer. An attention layer is then applied to evaluate the significance of these features. Finally, the muscle force output is generated through a dense layer.

3.2.1. Inverse kinematics

The varying positions and angles of IMUs worn by participants each time have a significant impact on the surrogate model in analysing human movement and even on assessing muscle fatigue. We refer to this impact as wearable errors. To mitigate wearable errors, an IK method, referred to as the IK strategy, is employed in the surrogate approach. This strategy optimally aligns the musculoskeletal model with the actual human posture. This is achieved by applying an inverse kinematic technique that minimises the sum of weighted squared errors in orientations. This method ensures a precise and accurate representation of human movements, which is essential for the effective implementation of the musculoskeletal model.

$$min \sum_{i \in IMU_S} \omega_i \, \theta_i^2 \tag{1}$$

where ω_i denotes the weight assigned to each IMU orientation and θ_i is the angular component of the orientation error between the measured orientation of a body segment by the IMU sensor and the actual orientation of that segment.

3.2.2. BiLSTM with attention mechanisms

SO is a prevalent technique in biomechanical and human motion analysis for estimating individual muscle forces. Muscle force or activation at each specific moment is calculated based on the observed human motion. This is achieved by solving motion equations for known movements and minimising the total muscle activation. The foundational equations for this process are as follows:

$$min \qquad \sum_{m=1}^{n} (a_m)^p \tag{2}$$

$$s.t. \qquad \sum_{m=1}^{n} (a_m F_m^0) r_{m,j} = \tau_j \tag{3}$$

$$\tau_i(q, \dot{q}, \ddot{q}) + \tau_e = \tau \tag{4}$$

where n represents the total number of muscles involved; a_m defines the activation level of muscle m at a specific time step; and F_m^0 is the maximum isometric force of that muscle. Additionally, $r_{m,j}$ refers to the moment arm of the mth muscle relative to the j^{th} joint axis; τ_j is the generalised force on the jth joint axis; $\tau_i(q, \dot{q}, \ddot{q})$ represents the joint torque generated by the joint angles, joint velocities, and joint accelerations; and τ_e denotes the external torque resulting from external loads. We assume that external loads are limited to the forces caused by holding objects. The external force is determined using techniques from our previous research (You et al., 2022), assessing whether the user is holding an object. If the distance between the hand and the object is less than 2 cm, the object is considered to be held, and a corresponding force is then applied to the hand.

SO, despite being effective, demands significant computational resources, making it unsuitable for real-time applications. To address this limitation, this paper introduces a surrogate model. This model is designed to approximate the function of the SO, achieving near real-time processing capabilities. This approach enables more efficient computation without compromising the accuracy of human motion analysis.

In this study, we utilise an IK-BiLSTM-AM network to model the correlation between human motion data and muscle force. The BiLSTM network, a variant of recurrent neural networks, is specifically designed to capture bidirectional long-term dependencies in time series data. Accurate estimation of muscle forces often necessitates an understanding of both past and future motion data.

The BiLSTM architecture processes the input sequence in both forward and backwards directions, thereby enhancing the network's understanding of the temporal context. This bidirectional processing can lead to more accurate predictions of muscle forces. Additionally, the relationship between motion data and muscle forces often extends over multiple time steps. This characteristic of BiLSTM potentially improves the muscle force estimation performance, making it a suitable choice for this application. BiLSTM comprises forward and backwards LSTM layers, each featuring a forget gate f_t, an input gate i_t, and an output gate o_t.

$$\begin{cases} f_t = \sigma\left(w_f x_t + U_f h_{t-1} + b_f\right) \\ i_t = \sigma(w_i x_t + U_i h_{t-1} + b_i) \\ o_t = \sigma(w_o x_t + U_o h_{t-1} + b_o) \end{cases} \tag{5}$$

where h_{t-1} represents the information obtained from the previous timestep in the time series, x_t is the input at the current time, the parameters w, U and b are the learnable weights and biases within the network, respectively, and the symbol σ denotes the activation function used in the network. Following this, the output of the LSTM cell is formulated as follows:

$$\begin{cases} c_t = f_t \otimes c_{t-1} \oplus i_t \otimes \left(tanh(w_c x_t + U_c h_{t-1} + b_c)\right) \\ h_t = o_t \otimes tahn(c_t) \end{cases} \tag{6}$$

where c_t denotes the output of the LSTM cell output state, and h_t denotes the cell output.

The forward layer of a BiLSTM layer is denoted as $\overrightarrow{\boldsymbol{h_t}} = [\overrightarrow{h_{t-n}}, \dots, \overrightarrow{h_{t-1}}]$, using the forward output layer sequence from time $t-n$ to $t-1$. Accordingly, the backward layer of a BiLSTM is denoted as $\overleftarrow{\boldsymbol{h_t}} = [\overleftarrow{h_{t-1}}, \dots, \overleftarrow{h_{t-n}}]$, using the backward output layer sequence from time $t-1$ to $t-n$. The final output of BiLSTM is denoted as:

$$\boldsymbol{h_t} = \overrightarrow{\boldsymbol{h_t}} \oplus \overleftarrow{\boldsymbol{h_t}} \tag{7}$$

where $\boldsymbol{h_t}$ is the concatenated vector that combines the outputs from both the forward and backward layers of BiLSTM. This vector serves as a representation of the hidden elements encompassing human motion information.

The attention mechanism in this framework evaluates the significance of features generated by the BiLSTM. This process enables the network to prioritise key movement features over less critical features. The additive attention mechanism is adapted in this work. Firstly, a fully connected layer is used for score computation:

$$e_t = w^T \tanh\,(W x_t + b) \tag{8}$$

where W and b represent the weights and biases of the attention mechanism; x_t represents the input at time step t; $\tanh$ is an activation function that introduces non-linearity, $w^T$is a weight vector that transforms the output of the activation into a scalar score e_t. Then a SoftMax normalisation is employed:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{j=1}^{T} \exp(e_j)} \tag{9}$$

where terms α_t denote the importance assigned to each feature; The SoftMax function converts the scores e_t into a probability distribution over all time steps, ensuring that the scores sum to 1.

$$o = \sum_{t=1}^{T} \alpha_t x_t \tag{10}$$

where o is a weighted sum of the input features x_t, where each feature is weighted by its attention score α_t.

The output generated by the AM layer is then input into a fully connected (FC) layer. This FC layer transforms the output from the AM into a suitable format for prediction. In our case, the FC layer processes the output from the AM layer and converts it into the final output size, corresponding to the number of muscles being analysed.

3.3. Human movement force-fatigue model

In this section, our focus is on exploring methods to estimate muscle fatigue based on specific historical muscle forces. We utilise a force-fatigue model grounded in first-order kinetics, which can be described by a first-order differential equation (Peternel et al., 2018b). This model comprises two aspects: first, an increase in fatigue level occurs when muscle force exceeds a certain threshold, with the rate of increase being directly proportional to the muscle force; second, a decrease in the fatigue index is observed when muscle force falls below this threshold, reflecting the process of physical recovery. The mathematical formulation of this model is presented as follows:

$$\frac{dv_m(t)}{dt} = \begin{cases} (1 - v_m(t))\dfrac{f_m(t)}{c_m} \; if \; f_m(t) \geq f_{th} \\ -v_m(t)\dfrac{R}{c_m} \; if \; f_m(t) < f_{th} \end{cases} \tag{11}$$

where $v_m(t)$ denotes the fatigue level of human muscle m, with a value ranging from 0 to 1; the term $f_m(t)$ represents the instantaneous force exerted by human muscle m; the recovery coefficient, denoted as R, is set at a value of 0.5, indicating the rate of recovery from fatigue; the threshold of muscular force about muscle m is represented by f_{th}; and c_m denotes the capability coefficient for muscle m, reflecting the muscle's resistance to fatigue, which varies across different parts of the human body. The value of C_m is formulate as:

$$C_m = -\frac{G_{ref} \cdot T_{end}}{\log(1 - 0.993)} \tag{12}$$

where G_{ref} represents the reference force, and T denotes the endurance time. The values of C_{ref} are chosen to correspond to 20% and 50% muscle activation.

Research by (Frey Law and Avin, 2010) highlighted that endurance time is specific to each joint and present a power model that characterises the relationship between endurance time and muscle force across different joints. This approach is employed to solve the function in Eq. (12) to determine the value of C_m. The formulation of this model is as follows:

$$T = b_0 G^{b_1} \tag{13}$$

where b_0 and b_1 are the parameters of the power model, which are determined based on specific body part.

3.4. HRC assembly task planner

In this section, we introduce a dynamic task planner designed to alleviate worker fatigue in manufacturing assembly activities through HRC. Based on the estimated physical fatigue of the workers' muscles, the planner is able to allocate tasks to different agents to mitigate the fatigue of workers. To simplify our experiment, we assume that there is only one robot and one worker in the experimental scenario. With simple parameter adjustments, our planner can be applied to multiagent task planning.

Our task planner incorporates an And-Or graph to represent the process of product assembly tasks, addressing the inherent challenges of complexity and uncertainty in the assembly process. Additionally, a dynamic task allocation model tailored for effective task planning is constructed. The And-Or graph can decompose complex assembly tasks into task units, commonly used for representing assembly tasks. Typically, an And-Or graph includes root nodes, nodes, or leaf nodes. The root node is used for representing an assembly task. An And node, which is denoted by " →", signifies that subtasks of the node must be executed in sequence. An Or node denoted by "||" indicates that the subtasks can be executed in parallel, and the leaf nodes represent executable task units. An example of an And-Or graph representing desktop PC assembly progression is shown in Figure 5. In the And-Or graph, based on its logic relationships, dependencies exist among task units. If task *a* is dependent on task *b*, *a* cannot occur in the absence of the occurrence of task *b* (Cheng et al., 2021). This dependency relationship imposes constraints on the progression and planning space of the task. Based on the And-Or graph, we define executable tasks as follows, which constitute the planning horizon in the task allocation model.

Executable tasks: a collection of task units that have no dependent tasks that have not yet been executed.

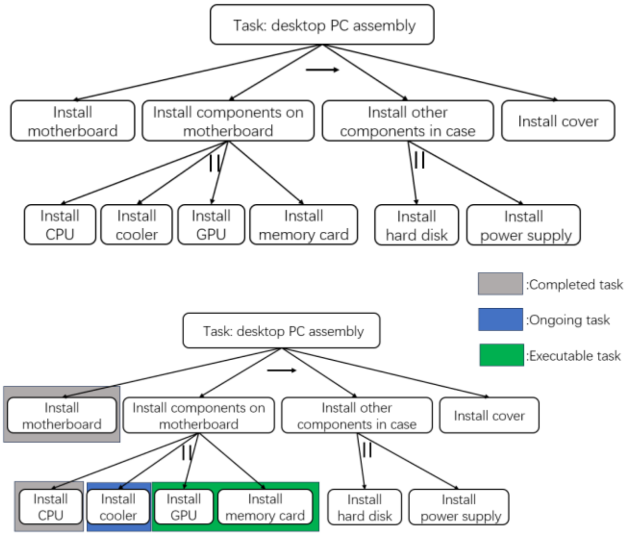

Figure 5. The upper graph represents an And-Or graph model for a desktop PC assembly task. There are And nodes and Or nodes, which are written as "→" and "||". The bottom graph shows an example of an executable task. The grey shading represents tasks that have been completed, the blue shading represents tasks that are ongoing, and the green shading represents tasks that are executable in the planning horizon of the planner.

The task planner dynamically plans the assembly tasks based on the estimated human muscle fatigue state. Initially, the planner identifies a set of executable tasks based on the And-Or graph model and passes them to the optimiser. Once an executable task is input, the optimiser optimises it based on the capabilities of humans and robots C_h, C_r and the current accumulated fatigue level of the human $\boldsymbol{F}_{acc}$, resulting in actions for both humans and robots a_h, a_r. The capability C_h, C_r refer to the types of actions they can perform. These actions are executed accordingly. After a_h, a_r is completed, the And-Or graph model and the optimiser will iteratively plan tasks until the assembly task is fully completed.

The optimiser is the core of the planner. With the input of executable tasks, the optimiser can allocate tasks that would be the most fatiguing to the workers to the robot and assign tasks that are less tiring to the workers. At the muscle level, the optimiser allocates tasks that require less use of fatigued muscles to the user, based on the worker's specific muscle fatigue. The optimisation problem is formulated as follows:

$$\min_{\boldsymbol{x},\boldsymbol{y}} \alpha_1(F_2^{max} - F_1^{max}) + \alpha_2(F_2^{mean} - F_1^{mean}) \tag{14}$$

$$s.t. \quad \sum_{j\in T} x_j + y_j = 1 \tag{15}$$

$$\sum_{j\in T-C_h} x_j = 0 \tag{16}$$

$$\sum_{j\in T-C_r} y_j = 0 \tag{17}$$

$$\sum_{j\in T} \boldsymbol{M}_{j,:} x_j + \boldsymbol{F}_{acc} \leq \boldsymbol{F}_2 \tag{18}$$

$$\sum_{j\in T} \boldsymbol{M}_{j,:} y_j + \boldsymbol{F}_{acc} \geq \boldsymbol{F}_1 \tag{19}$$

The goal of the objective, which is denoted as Eq. (14), is to allocate tasks that would be most fatiguing for human workers to the robot while assigning the least tiring task to the workers. The predicted fatigue value after the worker completes the most fatiguing task is denoted as $\boldsymbol{F}_1$, and the predicted fatigue value after completing the least fatiguing task is denoted as $\boldsymbol{F}_2$. The objective function is twofold. The first part focuses on the difference in maximum muscle fatigue levels between fatigue value F_2^{max} and F_1^{max}. The second part addresses the difference in mean muscle fatigue levels F_2^{mean} and F_1^{mean}. α_1, α_2 are weight indices. The decision variables $\boldsymbol{x}, \boldsymbol{y}$ are binary for the task allocation to the human and robot. T denotes the current executable actions. $T - C_h$ denotes the actions that humans cannot perform; $T - C_r$ denotes actions that robots cannot perform. $\boldsymbol{M}_{j,:}$ is the empirical fatigue in specific human muscles for task j. Equation (15) ensures that tasks are allocated either to a human or a robot. Equations (16) and (17) ensure that the tasks assigned to humans and robots are within their capabilities. Equations (18) and (19) define predicted muscle fatigue values for human $\boldsymbol{F}_1$ and $\boldsymbol{F}_2$.

4. Experiment

This section presents the experimental setup, evaluation criteria, and results used to validate the proposed method. The proposed method is evaluated with two experiments in a proof-of-concept task; (i) the accuracy of the presented method in estimating muscle forces of human activities is validated in experiment 1; and (ii) the effectiveness of physical fatigue mitigation of the HRC assembly task planner is validated with multisubject experiment 2. In both experiments, each subject is asked to complete a desktop personal computer (PC) assembly task, which contains a desktop PC case, motherboard, CPU, GPU, cooler, memory card, hard disk, power supply and cover. The experimental setup is shown in Figure 6 (top left). To emulate the physical demands faced by factory workers, our study used customised weights in desktop PC components ranging from 0.03 to 3kg, with an average of 1.3kg. The assembly requirements are presented in Figure 5. The motion of the subjects in the experiments was measured with IMU sensors (Xsens system). This experiment has been reviewed and approved by the School of Engineering Research Ethics Committee (reference: 2023-PGR-YY-R1).

In experiment 1, we collected real human motion data for training the IK-BiLSTM-AM network model. The accuracy of the proposed model was rigorously evaluated through comparisons with a range of conventional and state-of-the-art methods within this domain. In experiment 2, we validated the effectiveness of the assembly task planner in reducing participant fatigue and established a control group for comparative assessment through participation in repetitive desktop PC assembly tasks.

4.1. Experiment 1: the accuracy of the surrogate model

4.1.1. Experimental Setup

The aim of experiment 1 is to validate the effectiveness of the proposed surrogate model in replacing the SO method for the estimation of muscle force in HRC assembly. For the training of the surrogate model dedicated to muscle force estimation, a dataset encompassing human movement sensor data and muscle force data was compiled. This dataset was derived from a series of assembly actions performed by workers.

We initially recruited ten volunteers (5 males and 5 females, right-handed) who performed the desktop PC assembly tasks. To obtain human gestures, each volunteer wore a set of IMU sensors with an updating frequency of 40 Hz. Each volunteer is required to assemble the desktop PC three times, each consisting of 8 assembly actions, yielding a dataset consisting of 240 operation actions. The layout of the assembly workspace is shown in Figure 6. The assembly workspace encompasses both a parts zone and an operation zone. Following the assembly requirements depicted in Figure 5, they initially pick up the parts from the parts zone, return to the operation zone, and precisely place the parts in their corresponding positions. This process is repeated until the entire assembly operation is completed.

To derive muscle force data from a worker's assembly actions, the collected data were input into OpenSim 4.4, which is used for simulation computations. Within this framework, estimated muscle forces can be obtained through an SO approach. Additionally, the dataset was randomly divided, with 80% allocated for training and 20% for validation, ensuring a comprehensive analysis and assessment of the model's performance.

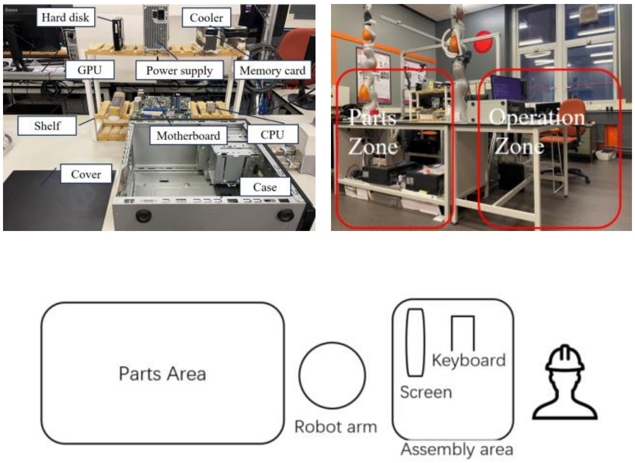

Figure 6. The top left graph shows the parts of the computer PC to be assembled, and the top right graph and bottom graph show the layout of the computer PC to be assembled.

4.1.2. Evaluation criteria and baseline

To evaluate the effectiveness of the proposed model, established evaluation metrics, including the root mean square error (RMSE), are utilised to quantify its performance. The RMSE is particularly useful for assessing the accuracy of predictions and is mathematically defined as:

$$RMSE = \sqrt{\frac{1}{T}\sum_{\tilde{t}=1}^{\tilde{T}}(y_{\tilde{t}} - \hat{y}_{\tilde{t}})^2} \tag{1}$$

where $y_{\tilde{t}}$ represents the ground truth and $\hat{y}_{\tilde{t}}$ denotes the corresponding predicted value at time t.

In our research, we carefully selected representative algorithms from the field to serve as benchmark methods for comparative analysis with our proposed model, thereby validating its effectiveness. Based on previous studies (Burton II et al., 2021; Sharifi Renani et al., 2021) demonstrating the success of deep neural networks (DNNs), long short-term memory (LSTM), and BiLSTM in predicting muscle force in biomechanical analysis, these methods were chosen for comparison. Additionally, the attention-convolution BiLSTM (AC-BiLSTM) (Liu and Guo, 2019) and transformer (Han et al., 2021) methods, which are known for their proficiency in handling sequential data tasks such as text classification, are also included as suitable comparators. To ensure a balanced comparison, we incorporated methods that are integrated with the IK strategy, identified by an "IK" prefix (e.g., IK-DNN). Our method without the IK strategy, which is named BiLSTM-AM, is also included. In total, there are 12 methods.

For the data preprocessing phase in the training of all methods, the StandardScaler technique from the sklearn library was utilised for standardisation. During the training phase, each method underwent 1,000 epochs to ensure thorough learning. All computational tasks were performed on an NVIDIA GeForce RTX 3060 GPU to leverage its robust processing capabilities.

4.1.3. Experimental Results of the Surrogate Model

Table 2 presents a comparative analysis of the estimated muscle force between the proposed methods and the baseline methods. This comparison is detailed in terms of both overall performance and representative muscle performance. The effectiveness of these methods is assessed based on classification accuracy, with the highest-performing results highlighted in boldface. In total, 12 methods are listed in Table 2, with our proposed method distinctly emphasised in bold. Since all participants were right-handed, the representative muscles listed in the table were on the right side of the body.

The IK-BiLSTM-AM model, which integrates the IK strategy, demonstrates superior predictive performance in overall muscle force prediction, achieving an accuracy that is at least 8% greater than that of other models. It particularly excels in evaluating representative muscles, outperforming most benchmark models. This superior performance indicates the model's ability to capture bidirectional temporal dynamics within input action sequences, thereby enhancing muscle force prediction accuracy. The model achieves an overall performance of 1.131 N, suggesting that while there is a slight reduction in accuracy compared to a purely SO approach, it remains acceptably accurate. Additionally, the IK-BiLSTM-AM model requires only approximately 0.048 seconds to process 1 second (40 frames) of data; in contrast, the SO method takes approximately 43.18 seconds. This indicates that the proposed surrogate model successfully meets the dual demands of accuracy and real-time assessment of muscle forces in the context of HRC. Notably, all methods utilising the IK strategy exhibit enhanced estimation performance over their non-IK counterparts. This outcome underscores the effectiveness of the IK strategy of our method in mitigating wearable errors.

Table 2. RMSE evaluation results for the proposed method and baselines on overall and representative muscles

Methods	Overall	Deltoid Anterior	Biceps short	Triceps medial	Pectoralis major
DNN	1.376	1.711	3.010	0.333	1.474
IK-DNN	1.368	1.499	3.164	0.301	1.364
LSTM	1.557	1.940	3.678	0.285	1.168
IK-LSTM	1.340	1.533	3.326	0.272	1.282
BiLSTM	1.398	1.594	3.075	0.237	0.981
IK-BiLSTM	1.232	1.590	3.161	0.232	1.072
AC-BiLSTM	1.547	1.644	3.217	0.235	1.165
IK-AC-BiLSTM	1.428	**1.203**	2.749	0.222	1.388
Transformer	1.924	1.709	3.934	0.288	1.412
IK-Transformer	1.872	1.820	3.633	0.291	1.384
BiLSTM-AM	1.212	1.909	2.704	0.220	1.071
IK-BiLSTM-AM	**1.131**	1.282	**2.651**	**0.205**	**0.915**

4.2. Experiment 2: The effectiveness of the task planner

The objective of Experiment 2 is to validate the effectiveness of the proposed planner in reducing human physical fatigue in a real human-robot collaborative assembly scenario.

4.2.1. Experiment setup

For this experiment, we recruited 12 participants (6 males and 6 females, all right-handed), different from those in Experiment 1, to participate in a desktop PC assembly task. The layout of the assembly operation is illustrated in Figure 6. Unlike the solo assembly layout in Experiment 1, the human-robot collaborative operation zone included a collaborative robot, a screen, and a keyboard. During the experiment, the planner was utilised to allocate tasks to different agents. Tasks assigned to the robot were executed by a Kuka iiwa robot arm, while tasks assigned to human participants were prompted on the screen. Participants completed actions as indicated by the prompts. Participants reported the completion of tasks by pressing keys on a keyboard. The assembly requirements were identical to those of Experiment 1. We advocate for flexible HRC, where humans are not strictly obliged to follow the planner's suggested actions. However, to validate our proposed method, we assumed that participants adhered to the actions prompted by the planner.

A control group was established for the experiment. The planner in the control group employed a random strategy, with all other settings being identical to those in the experimental group. The strategy in the experimental group was the optimisation strategy. In the random strategy, the planner randomly assigns executable tasks to either humans or the robot based on assembly task progression and user capabilities.

Each participant engaged in both the experimental and control group settings, with a half-hour sitting rest interval between each session. In both the experimental and control groups, every subject was required to assemble eight desktop PCs. After each desktop PC is assembled, it is disassembled by another human user, restoring it to its initial setup to simulate an assembly line process. The order in which participants undertook the experiments was randomly determined. Participants were blinded to the type of experiment they were participating in.

After completing both the experimental and control groups, each participant was required to complete a questionnaire to evaluate the subjective fatigue of the participants, which will be used in the comparison analysis with the fatigue data from the human digital twin model to validate the effectiveness of physical fatigue mitigation of the HRC assembly task planner. The questions in the questionnaire are listed in Table 3.

Table 3. The questions in the questionnaire for subjective fatigue evaluation

No.	Details
Question 1	Question 1 in the questionnaire is the Modified Borg Scale (Wilson and Jones, 1989), with a score ranging from 0 to 10, to assess the physical exertion required to complete the tasks. To evaluate whether there was a significant difference between the experimental and control groups, a Wilcoxon signed-rank test was conducted, and the significance level was $\alpha = 0.05$.
Question 2	During the experiment, which area did you feel fatigued? Please mark on the attached human body diagram. (Image not included)
Question 3	After approximately how many rounds did you begin to feel fatigued? Possible responses range from 1-8, or 'not fatigued.'

In this experiment, the task planner parameters were established as follows: $\alpha_1 = 0.5$ and $\alpha_2 = 0.5$. $T - C_h$ is $\emptyset$. $T - C_r$ has a CPU, a motherboard, and a cover. The optimisation model driving the task planner utilised the Gurobi solver for solution determination. Optimal solutions were displayed to the users via the task planner's GUI as a form of task guidance. The GUI layout is illustrated in Figure 7. The left side pane of the GUI presents a task tree to display the status of the assembly tasks, while the right side provides prompts for agents based on the task status. The experimental process and the corresponding digital twin model are shown in Figure 8.

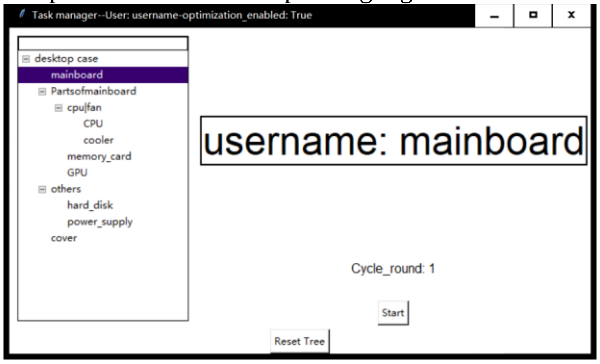

Figure 7. The GUI of the task planner in the desktop assembly task. The left side is a task tree. On the right side is a prompt for the user, which contains the username and part to be assembled. The cycle round indicates how many rounds of tasks have been conducted. The start button is used to start a task. The reset tree button is used to reset a new task.

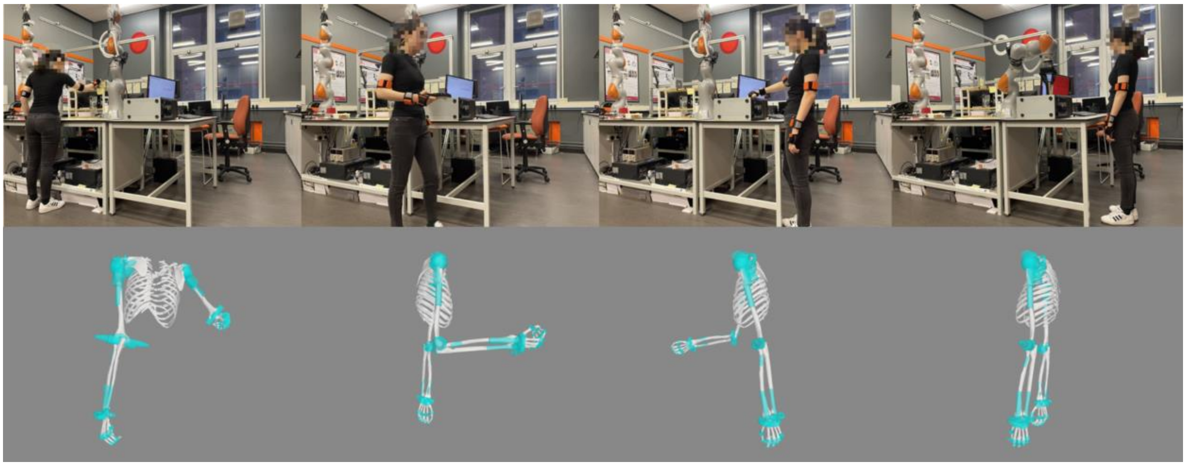

Figure 8. The process of human-robot collaborative assembly of the desktop PC and its corresponding digital twin human model is depicted from left to right as follows: a human picks up parts in the parts area, transports parts to the assembly area, assembles the parts, and waits for the robot to assemble parts.

4.2.2. Results and discussion

Initially, the results of the modified Borg scale questionnaire were subjected to a Wilcoxon signed-rank test, yielding a p-value of 0.0049, which is less than 0.05. This outcome indicates a significant difference in perceived exertion between the optimisation and random strategies in the desktop PC assembly experiment.

We discussed the experimental results by comparing the results from the questionnaire and results from the digital twin model to assess the effectiveness of the proposed method in fatigue evaluation and mitigation within assembly tasks. According to the fatigue assessment model presented in this paper, the maximum (mean 0.38) and average (mean 0.10) muscle fatigue levels at the muscle layer for 12 participants under the optimisation strategy in the desktop PC assembly were significantly lower than those under the random strategy (maximum mean of 0.89, average mean of 0.22), as shown in Figure 9 (top left). In line with question 1 of the Modified

Borg Scale, the box plot in Figure 9 (top middle) indicates that participants generally perceived lower exertion (mean 2.2) with the optimisation strategy than with the random strategy (mean 4.4). Furthermore, responses to question 2, covering both the instances of non-fatigue subjects (optimisation strategy: 6, random strategy: 1) and the rounds at which fatigue was first felt (optimisation strategy, mean: 6.3; random strategy, mean: 4.5), suggest that the optimisation strategy is effective in mitigating fatigue under equivalent tasks. The results are shown in Figure 9 (top right). The results from both questionnaires are consistent with the findings of the proposed fatigue model in terms of fatigue reduction. These findings validate the application potential of the proposed fatigue assessment model in evaluating fatigue and confirm the effectiveness of the proposed task planner in reducing fatigue.

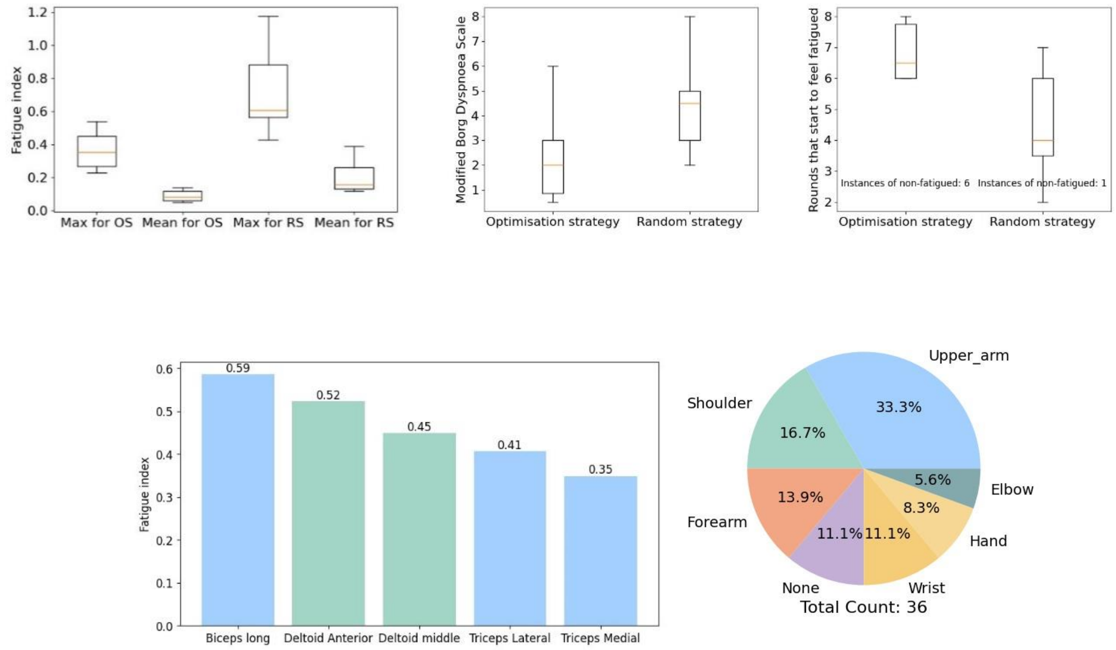

Figure 9. The top left graph displays box plots of the maximum and average muscle fatigue levels at the muscle layer for 12 participants under both the optimisation strategy (OS) and random strategy (RS). The top middle graph shows the box plots based on question 1 of the Modified Borg Scale, comparing the results of the two strategies. The top right graph illustrates the box plots for the number of rounds participants felt fatigued as question 2 of the questionnaire. The bottom left graph displays the top five muscles with the highest average fatigue levels across all participants. The bottom left graph depicts the five muscles with the highest average fatigue levels in each participant. Finally, the bottom right graph summarises the fatigued areas reported in question 3 of the questionnaire. The muscles depicted in the graphs are located on the right side of the body.

Regarding specific muscle groups, our fatigue model calculated the average muscle fatigue levels across all participants and identified the five most fatigued muscles as follows: Biceps Long, Deltoid Anterior, Deltoid Middle, Triceps Lateral, and Triceps Medial. For more details, please refer to Figure 9 (bottom left). Additionally, through question 3, we compiled data from 24 questionnaires, resulting in 36 fatigued results, and created a pie chart depicted in Figure 9 (bottom right). The most frequently reported fatigued areas were the upper arm (33.3%) and the shoulder (16.7%). The Biceps Long, Triceps Lateral, and Triceps Medial are part of the upper arm, and the Deltoid Anterior and Deltoid Middle are part of the shoulder. The comparison between the two sets of results demonstrated a congruence between the fatigue areas reported subjectively by participants and those identified through the fatigue model calculations. This correlation further validates the effectiveness of the proposed method in accurately determining fatigue in specific muscle groups.

The experimental results demonstrate the efficacy of the proposed method in estimating and optimising fatigue in assembly tasks, both overall and in specific areas. The authors believe that this method will show even more significant results in fatigue optimisation over longer durations in assembly experiments.

5. Conclusion

Physical fatigue in humans has a profound impact on HRC in manufacturing, influencing worker well-being. To address this concern, this paper presents a musculoskeletal model-based human digital twin for muscle force estimation, followed by the integration of a force-fatigue model to assess muscle-level physical fatigue in HRC assembly tasks. Subsequently, a fatigue-aware task planner is proposed for physical fatigue reduction. In the task planner, an And-Or graph is utilised to model the assembly tasks, and a corresponding optimisation model is developed to allocate tasks among multiple agents. The efficiency of the surrogate approach has been validated in a proof-of-concept assembly experiment, indicating that it is at least 8% more accurate than benchmark methods. The role of the task planner in alleviating worker fatigue has been validated through the participation of multiple subjects in the assembly experiment. These outcomes underscore the potential of the proposed approach for applications in HRC assembly.

As an exploratory study, the task planner proposed in this paper focuses solely on mitigating human fatigue. While this approach addresses the fatigue alleviation problem, it may not fully meet the complex requirements of real-world HRC tasks. To address this limitation, future work will involve developing a multi-objective task planner. This planner will incorporate factors such as fatigue, time efficiency, and safety into collaborative tasks. Additionally, the optimisation model should be refined to support a multi-objective framework, integrating these various factors into the objective function.

The force-fatigue model used in this study is a general model with parameters derived from empirical data based on different body parts. While this general model has effectively mitigated human fatigue, future work should focus on developing worker-specific models. A promising approach is to fine-tune the model parameters using reinforcement learning, thereby creating personalized force-fatigue models tailored to individual workers.

Furthermore, the current study's validation is based on a proof-of-concept experiment conducted in a controlled laboratory environment. To advance the application of this research, validation in a more complex, factory-like environment is necessary. To solve this limitation, future work should also focus on testing the extended task planner on more complex tasks to evaluate the scalability of the proposed approach for real industrial applications.

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