Human digital twin for real-time physical fatigue estimation in human-robot collaboration

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***Abstract*—Human-robot collaboration is a vital approach in manufacturing, integrating the capabilities of both humans and robots effectively. In recent years, the well-being of manufacturing workers has received increasing attention with the development of manufacturing systems. However, the perception of human characteristics, such as physical fatigue, and the integration of these characteristics with human-robot manufacturing systems, remain relatively limited. The lack of awareness regarding human physical fatigue may negatively impact workers' health and, in severe cases, lead to musculoskeletal disorders. To overcome this bottleneck, this paper presents a human digital twin method for real-time fatigue estimation in a manufacturing scenario. Firstly, we adopt a human muscle force estimation method to simulate the upper limb muscle activity of humans during assembly activities. Secondly, an IK-BiLSTM-AM based surrogate model is used to accelerate the process of estimating the muscle state. Lastly, we adopt a muscle force-fatigue model for real-time muscle fatigue assessment. This scheme is validated through a proof-of-concept experiment in a manufacturing activity dataset. The findings highlight the efficiency and resilience of the suggested approach.**

Keywords—physical fatigue, digital twin, human-robot collaboration

I. Introduction

In manufacturing systems, automation has not yet been able to completely replace manual labour due to factors such as task diversity, agent capabilities, and costs [1]. As a result, human-robot collaboration (HRC) has attracted significant attention as a manufacturing paradigm, integrating the advantages of human flexibility and the strength and repeatability of robots [2]. Under this paradigm, different agents work together to complete shared manufacturing tasks within a shared space.

However, research on workers' fatigue or comfort during human-robot collaboration is very limited, let alone incorporating it into the HRC system [3]. Although the presence of robots has replaced some manual tasks, the lack of perception and decision-making regarding human fatigue may inevitably lead to worker fatigue. In severe cases, fatigue may cause musculoskeletal disorders, affecting an individual's well-being. Implementing task planning to alleviate human fatigue is highly challenging, primarily due to the lack of a real-time, muscle-level method for perceiving human physical fatigue [4].

Digital twin is an advanced technology considered to be one of the enablers of Industry 4.0. Human digital twin models represent virtual representations of individuals aimed at enhancing productivity, improving skills, and integrating into advanced manufacturing systems. Many studies [5] are utilizing the digital twin technology in the development of safe and seamless human-robot collaborative manufacturing systems.

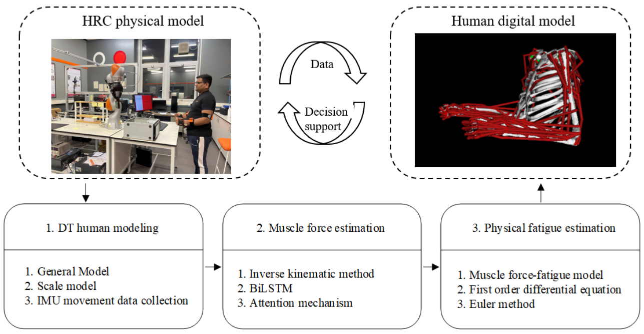

Fig. 1. The framework of the human digital twin method for physical fatigue estimation

However, current human digital twin models for human physical fatigue have certain limitations in meeting the requirements of real-time and muscle-level fatigue assessment. For instance, subjective assessment methods, e.g., the Borg RPE scale[6], may lead to inaccurate evaluation results and disrupt the normal workflow, while ergonomic methods, e.g., Rapid Upper Limb Assessment [7], are challenging in capturing individual variations in human physical fatigue. Additionally, there are integration challenges with manufacturing systems. Therefore, the development of a real-time muscle-level physical fatigue assessment method is urgently needed to address the demands of human-robot collaborative manufacturing systems.

Given the limitations of the analysis, this paper introduces a muscle-level physical fatigue assessment method for manual workers. The framework is illustrated in Fig. 1. This technique combines biomechanical analysis and a bidirectional Long Short-Term Memory (BiLSTM) network, utilizing inertial Measurement Unit (IMU) data as its input. Firstly, we adopt a human muscle force estimation method to simulate the upper limb muscle activity of humans during assembly activities. Secondly, a BiLSTM-based surrogate model is used to accelerate the process of estimating the muscle state. Lastly, we adopt a muscle force-fatigue model for real-time muscle fatigue assessment. A proof-of-concept experiment is designed to validate the proposed methods.

The contribution of this paper is summarized as follows:

(1) An IK-BiLSTM-AM based human digital twin model is built, combining a force-fatigue model, to assess workers' physical fatigue during manufacturing activities.

(2) The proposed IK-BiLSTM-AM method that estimates human muscle force and physical fatigue is validated in a real manufacturing experiment.

II. Literature review

A. DT Modeling Techniques for HRC

Digital Twin, a critical technology for realizing Industry 4.0 and intelligent manufacturing, is garnering growing interest from both academic and industrial sectors [8]. The modelling technology of digital twins is of paramount importance in their development and applications [9]. This section briefly reviews the modelling techniques of human-robot collaboration based on digital twins.

Depending on the target objects, modelling techniques of human-robot collaboration based on digital twins can be classified into three categories: objects, robots, and humans. Object-based modelling includes techniques for modelling objects in the manufacturing environment, such as product parts and tools. Object modelling typically involves modelling the geometric, physical, and behavioural properties of physical objects in a virtual space to define the object's shape, materials, and physical reactions during operation. Commonly used modelling software includes SolidWorks, Blender, and Unity. To achieve dynamic mapping between physical objects and virtual replicas, object recognition and tracking based on machine vision have received a great deal of research [10]. Robot simulation environments provide a basis for digital twin modelling of robots, such as ROS/Gazebo, MATLAB Simulink, etc. Based on this, many digital twin-based robot modelling techniques have been developed, such as adaptive control techniques for robots under human-robot collaborative environments [11]; fast programming techniques through demonstration learning [12]; and autonomous learning based on reinforcement learning [13]. The human digital twin model mainly includes predictive and cognitive models, which are used to simulate and predict human thought processes and reactions under various situations, such as action recognition under specific manufacturing tasks [14] and intent recognition of human operators [15], thereby developing safe and efficient human-robot collaborative systems.

In the field of biomechanics, biomechanical analysis techniques based on muscle-skeleton models have been widely used in the medical, sports, and human engineering fields. To our knowledge, few studies have introduced them to human-robot collaborative tasks in the manufacturing environment [16]. Analyzing biomechanical aspects, like the muscle forces of operators, is crucial for comprehending their activities and performance [17]. It has the potential to enhance the user experience of operators in human-robot collaboration tasks under manufacturing and the decision-making process of robots. Therefore, as a pilot study, the focus of this article is to develop a human digital twin model based on the muscle-skeleton model and its application in task planning in human-robot collaboration to alleviate human fatigue [18].

B. Human physical fatigue assessment methods

High physical-demand manual workers are at an elevated risk of musculoskeletal disorders, particularly those working on assembly lines or in the construction industry[19]. The primary cause is prolonged repetitive work, especially involving the same hand or arm actions. Effective fatigue management is a useful method that can be applied in the workplace to reduce such risks. Numerous methods have been proposed for physical fatigue measurement, including subjective reports and objective measurements. However, these methods do not fulfil the requirements for continuous, automatic, and accurate physical fatigue assessment.

Subjective methods involve workers reporting their physical fatigue levels based on their feelings while working. Examples include the Borg RPE scale and the Borg CR10 scale[6]. However, these methods have drawbacks: (1) the assessment results may be inaccurate, and (2) the assessment may interrupt normal work. Objective methods are categorized as physiological indicators, ergonomic methods, and biomechanical methods. Human physical activity is a physiological process; thus, human fatigue can be assessed by physiological signals, such as heart rate [20] and sEMG [21]. However, these physical fatigue assessment methods usually require specific sensors attached to the human body.

Ergonomic methods aim to assess worker fatigue, allowing users to engage in repetitive motions comfortably and reducing the risk of injury. Examples include the Rapid Upper Limb Assessment and Rapid Entire Body Assessment[7]. The main limitation of ergonomic methods is the inaccuracy in assessing human body fatigue. These models do not consider human anthropometry, which can affect assessment results' accuracy. Furthermore, these methods rely on simplified anatomy in fatigue assessment, which may not model the complexity and variability of human behaviour [22]. Consequently, the assessment results from different methods may be inconsistent.

Musculoskeletal models are digital twins of human bodies, consisting of computational models of the body and its functions [23]. Musculoskeletal modelling is a prevailing method for biomechanical fatigue assessment by simulating bones, joints, and muscles during physical activities. These simulations provide insight into the physical strains experienced, contributing to physical fatigue development[24]. The complexity of musculoskeletal models typically requires multiple data sources, including human body movement and contact forces, resulting in lengthy preparation times, even for domain experts. Additionally, the analysis of musculoskeletal models demands high computational resources [25]. These factors limit the applicability of musculoskeletal models for real-time physical fatigue assessment in various scenarios. Lowering the barriers to adopting this technology in HRC and enhancing the practicality of the method are of paramount importance, and they are the focal points of this study.

III. Methodology

This paper aims to propose a real-time continuous physical fatigue assessment method, which can be used in the decision-making of HRC in the industry. The pipeline of the proposed method is shown in Fig 1. Firstly, a DT human model is initialized by scaling the musculoskeletal model, driven by movement data captured by IMU sensors. Secondly, an IK-BiLSTM-AM network, which integrates the biomechanical analysis and deep neural network, is used to estimate human muscle forces as a surrogate model of static optimization based on the musculoskeletal model and the IMU data. Lastly, muscle-level fatigue can be estimated based on a muscle force-fatigue development model.

A. *Musculoskeletal DT modelling*

Computational musculoskeletal simulations are extensively employed to assess the contribution of muscles in human motion. To realize muscle level fatigue analysis, we used this method to estimate the contribution of muscle force to the movement of humans. Because manual work mainly requires the movement of the upper limb, this paper focuses on the movement of the upper limb of humans. We adopt a muscle skeleton model, namely, the bimanual upper arm model [26] to meet the requirements of movement analysis. Based on that, we can simulate bonds, joints, and muscles of human motion, with the input of human motion data and external force.

The kinematic foundation for the dynamic model included the glenohumeral joint, elbow, forearm, wrist, thumb, and index finger, positioning the hand in a grip posture and fixing the degrees of freedom at the index finger and thumb. The model has 28 degrees of freedom in total and is symmetric. The dimensions of each joint of the bimanual upper arm model are scaled to match the dimensions of subjects by anthropometry for manual measurement.

To accurately capture the movement of human upper limbs, we use inertial measurement units (IMUs) to measure human movement data. For each experimental subject, nine IMUs are pasted on the chest, scapula, upper arm, forearm, and hand of the human body, as shown in Fig 2. Each IMU is mapped to a human body segment.

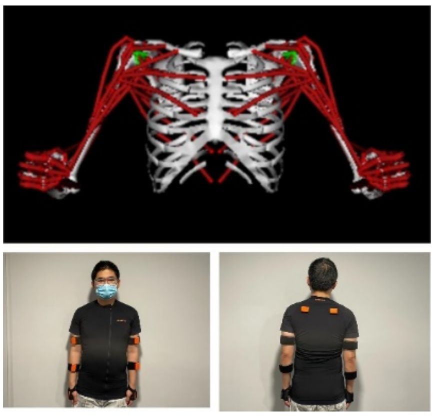

Fig. 2. Upper Limb Musculoskeletal Model; Participants were equipped with Xsens IMUs sensors for the demonstration.

B. *Muscle activation/force estimation*

Through biomechanical analysis, we can effectively estimate the force exerted by human muscles. However, the computational complexity of this method results in a time-consuming process, making it unsuitable for real-time applications. To address this, advanced deep learning techniques have been employed as an alternative, standing in for traditional biomechanical computations. Traditional LSTM networks are designed for processing sequential historical data, but they perform less satisfactorily when it comes to capturing future contextual information. This limits their capacity to extract specific features within the movement data. Furthermore, the features of motion data are interrelated, and their significance levels vary. LSTMs struggle to extract this nuanced information, compromising the accuracy of the predicted muscle forces. This paper integrates inverse kinematics analysis (IK), BiLSTM, and Attention Mechanism (AM), introducing a new network structure, named IK-BiLSTM-AM, to overcome the aforementioned limitations. Within this framework, IK is utilized to translate sensor signals into joint rotation and translation data of the human body. The BiLSTM focuses on analyzing the contextual information in human motion data to extract movement features, while the AM gauges the significance of these movement features, enhancing the mapping between movement characteristics and muscle forces.

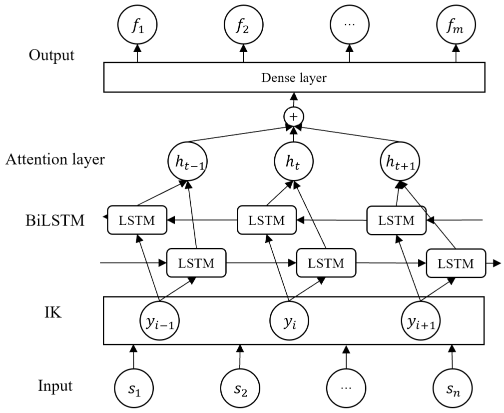

Fig. 3. The structure of the proposed IK-BiLSTM-AM method

(1) Inverse kinematics

To minimize noise errors produced during the wearing process of IMU, an IK method is applied in the surrogate method, which is called the IK strategy. To best match the muscle skeleton model and human posture, an inverse kinematic method is applied by minimizing the sum of weighted squared errors of orientations at each time step t.

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

where w_i denotes the weight corresponding to each IMU orientation, and θ_i are the angle components of the orientation errors.

(2) BiLSTM with attention mechanisms

Static optimization is a widely used approach to estimate individual muscle forces in biomechanical and human motion analysis. Static optimization is a technique for calculating muscle force or activation at each moment based on known human motion by solving the motion equations for the known motion and minimizing the sum of muscle activations. The corresponding equations are as follows:

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

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

where n represents the total number of muscles; a_m denotes the activation level of muscle m at a specific time step; F_m^0 is the maximum isometric force of that muscle; $r_{m,j}$ is its moment arm related to the j^{th} joint axis.

However, static optimization requires high computation, so it cannot meet the requirements of real-time applications. In this paper, we build a surrogate model, which approximates the function of static optimization with a nearly real-time processing capability.

We adopt an IK-BiLSTM-AM network to model the relationship between human motion data and muscle force. BiLSTM, a type of recurrent neural network, is designed to learn bidirectional long-term relationships across time steps in time series data. Muscle force estimation often requires the understanding of both past and future motion data to predict the forces accurately. BiLSTM processes the input sequence both forwards and backwards, enhancing the comprehension of temporal context and potentially yielding more precise force predictions. Besides, the relationships between motion data and muscle forces can span across multiple time steps. BiLSTM can capture these long-range dependencies more effectively than traditional RNNs or unidirectional LSTM, which can improve the force estimation performance.

BiLSTM has one forward and backward LSTM layer, which has forgotten gate f_t, input gate i_t and output gate o_t.

$$\begin{cases} f_t = \sigma\left(w_f x_t + U_f h_{t-1} + b_f\right) \\ i_t = \sigma(w_i x_t + U_i h_{t-1} + b_i) \\ o_t = \sigma(w_o x_t + U_o h_{t-1} + b_o) \end{cases} \tag{4}$$

where h_{t-1} denotes the information from the previous time series; x_t is the input at the current time; w, U and b are the network parameters to be learned; σ denotes the activation function. Then the long-term memory c_t and short-term h_t then formulated as follows:

$$\begin{cases} c_t = f_t \otimes c_{t-1} \oplus i_t \otimes \left(tanh(w_c x_t + U_c h_{t-1} + b_c)\right) \\ h_t = o_t \otimes tahn(c_t) \end{cases} \tag{5}$$

where h_t is the concatenated vector of the outputs of the forward and backward process of BiLSTM. It represents the hidden elements of the human motion information and is written as follows:

$$h_t = \overrightarrow{h_t} \oplus \overleftarrow{h_t} \tag{6}$$

The attention mechanism assesses the importance of features output by BiLSTM, allowing the network to focus on crucial movement features rather than secondary ones. At its core, the attention mechanism consists of a fully connected layer and a softmax layer, represented as follows:

$$e_t = w^T \tanh\left(W x_t + b\right) \tag{7}$$

$$\alpha_t = \frac{\exp\left(e_t\right)}{\sum_{j=1}^{T} \exp\left(e_j\right)} \tag{8}$$

$$o = \sum_{t=1}^{T} \alpha_t x_t \tag{9}$$

where W and b denote weights and biases respectively, α_t indicates the importance, and o is the output of the attention layer.

The output from the Attention Mechanism (AM) layer is subsequently fed into a fully connected (FC) layer. This FC layer functions to transform the output of the AM cells into the prediction space. It consists of a linear transformation of the AM output with the optional application of a non-linear activation function. Here, the FC layer takes the output from the AM layer and transforms it into the output size, which is the number of muscles.

C. Human movement fatigue model

In this section, we commence by examining methodologies for estimating the degree of muscle fatigue, relying on the specific muscular strength and corresponding historical data. We adopt a fatigue model underpinned by first-order kinetics, expressible as a first-order differential equation [27]. This model is bifurcated into two key components: firstly, when the muscle force surpasses a given threshold, there is an augmentation in the fatigue level, with the increment positively correlated with the muscle strength; secondly, when the muscle force is beneath this threshold, the fatigue index diminishes in tandem with physical recuperation. The representation of the equation is as follows:

$$\frac{dv_m(t)}{dt} = \begin{cases} \left(1 - v_m(t)\right) \frac{f_m(t)}{c_m} & if\ f_m(t) \geq f_{th} \\ -v_m(t) \frac{R}{c_m} & if\ f_m(t) < f_{th} \end{cases} \tag{10}$$

Here, $v_m(t)$ signifies the degree of fatigue in the human muscle m, its value lies between zero and one; $f_m(t)$ symbolizes the instantaneous muscular force of human muscle m; R denotes the recovery coefficient, having a value of 0.5; f_{th} represents the threshold of muscular force about muscle m; c_m stands for the capability coefficient associated with muscle m, representing muscle fatigue resistance capability among the different parts of the human body.

$$C_m = -\frac{G_{ref} \cdot T_{end}}{\log\left(1 - 0.993\right)} \tag{11}$$

The term G_{ref} is referring to the reference force, while T stands for the endurance time. The literature[28], emphasizing that time is joint-specific, introduces a power model that describes the relationship between the endurance rest time and muscle force across various joints, which is as follows.

$$T = b_0 G^{b_1}$$

We selected values from states of 20% and 50% muscle activation to compute C_F. Consequently, we have achieved a quantitative representation of the degree of muscle fatigue.

IV. Experiment

This section introduces the experimental setup, evaluation criteria, and results for the validation of the proposed framework. Firstly, we validate the accuracy of the presented method in estimating muscle forces of human activities. We collect real human motion data for the training of the IK-BiLSTM-AM network model in a real-world scenario. The model's accuracy is subsequently benchmarked against both traditional and cutting-edge methodologies in the domain. Additionally, we examine the accumulation of fatigue in different muscles throughout "pick and place" tasks by assessing muscle forces during human activities.

A. Experimental Setup

This study selects a typical "pick and place" action in the assembly task to validate the proposed method. Such pick-and-place tasks are commonly required in assembly scenarios.

We initially have 10 volunteers, who perform operations while wearing IMU sensors. IMU sensors belong to the Xsens system, and data is collected at a frequency of 40 Hz. Each volunteer conducts 24 pick-and-place operations, yielding a dataset consisting of 240 operation actions. To train the surrogate model for muscle force estimation, muscle force data is needed. The collected data is then input into OpenSim 4.4 for simulation, where estimated muscle forces are obtained using a static optimization approach.

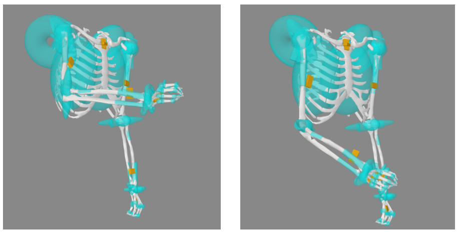

Fig. 4. The simulation process of pick and place of participants.

The simulation process is shown in Fig. 4. The dataset is randomly split into 80% for training and 20% for validation.

B. Evaluation criteria and baseline

To assess the efficacy of the proposed model, the root mean square error (RMSE), is employed to quantify the performance of the method. Specifically, RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{T}\sum_{\tilde{t}=1}^{\tilde{T}}(y_{\tilde{t}} - \hat{y}_{\tilde{t}})^2} \quad (12)$$

where $y_{\tilde{t}}$ and $\hat{y}_{\tilde{t}}$ denote the ground truth and the corresponding predicted value, respectively.

In this paper, representative algorithms from the field are selected as the baseline methods for comparison with the proposed method. Previous research [29], [30] has shown the efficacy of DNN, LSTM, and BiLSTM methods in predicting muscle force of biomechanical analysis, thus these methods were chosen for comparison. The AC-BiLSTM [31] and Transformer [32] methods have demonstrated their effectiveness in handling sequential data tasks, such as text classification, making them suitable comparators as well. To ensure a fair comparison, methods integrated with the IK strategy were also included as benchmark techniques, designated with an "IK" prefix, e.g., IK-DNN. For data preprocessing during the training of all methods, the StandardScaler method from sklearn was employed for standardization. Throughout the training process, each method was subjected to 1,000 epochs of iteration. All computations were executed on an NVIDIA GeForce RTX 3060 GPU.

C. Experiment Result of Surrogate Model

As depicted in Table 1, the comparison results of estimated muscle force from the proposed methods and baseline methods are shown in terms of overall performance and specific muscle evaluation. The experimental results are evaluated in terms of classification accuracy. The best results and name of our method are shown in boldface. In total, there are 12 methods shown in the Table 1.

The proposed IK-BiLSTM-AM model, employing the IK strategy, outperforms the other models in terms of overall prediction results. The evaluation results for the representative muscles are mostly superior to the majority of other models, meaning BiLSTM with attention mechanism is capable of capturing the bidirectional temporal characteristics of input action sequences for better muscle force prediction. The proposed model achieves 1.131 N in overall performance. This suggests that, although the model's accuracy is somewhat reduced compared to the simulation approach, it remains within an acceptable range. The proposed surrogate model can meet the requirements for accuracy and real-time assessment of muscle forces in human-robot collaboration. In particular, all methods using the IK strategy show better predictive performance than equivalent methods without the IK strategy. This suggests that the IK strategy can effectively combat the noise error produced during the wearing process of inertial measurement units.

TABLE I. RMSE EVALUATION RESULTS FOR THE PROPOSED METHOD AND BASELINES ON OVERALL AND REPRESENTATIVE MUSCLES

Method	**Overall**	**Del1**	**Bic2**	**Tri3**	**Pec1**
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**

[a] Del1 denotes Deltoidc Anterior; Bic2 denotes Biceps short; Tri3 denotes Triceps medial; Pec1 denotes Pectoralis major Clavicular.

D. Fatigue model

In this section, we employ the force fatigue model to investigate the accumulation of physical fatigue in workers during the pick-and-place task. Within this model, f_{th} is set to 2% of the maximum muscle force. We collect data from

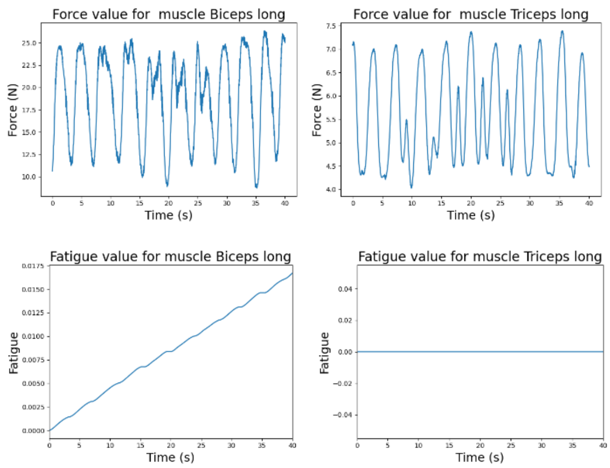

Fig. 5. Selected muscle force and fatigue accumulation in pick and place

a sequence of "pick and place" motions, calculating the associated muscle forces and fatigue accumulation. The force and fatigue levels of selected muscles are shown in Figure 5. The Biceps Long accumulated around 1.75% fatigue. In contrast, the force exerted by the Triceps Long remained consistently below f_{th} , resulting in zero accumulated fatigue.

These results suggest that the fatigue model can serve as an indicator of fatigue during human-robot collaboration. In future work, we will conduct more human-robot collaboration experiments to further validate the model's effectiveness and accuracy.

V. 5. Conclusion

Human physical fatigue is a key factor of HRC manufacturing, which may influence the well-being of workers. To address this, the paper proposes the IK-BiLSTM-AM-based digital twin approach to estimate muscle fatigue during human-robot collaboration. This method is well validated in a real manufacturing experiment in terms of accuracy by comparing it with baseline methods. The results underscore the promising application potential of the proposed framework in human-robot collaboration scenarios, suggesting that the fatigue model can serve as an indicator of fatigue during human movement activity. In the future, we plan to set up a human-robot collaboration experiment to further verify this method.

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