2024 IEEE International Conference on Robotics and Automation (ICRA 2024)
May 13-17, 2024. Yokohama, Japan

Human-Exoskeleton Locomotion Interaction Experience Transfer: Speeding up and Improving the Performance of Preference-based Optimizations of Exoskeleton Assistance During Walking

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***Abstract*— Preference-based optimizing methods have shown their advantages and potential in exploring individual, comfortable, and effective control strategies and assistance parameters of exoskeletons during locomotion. Research indicates that compared with naive wearers, knowledgeable wearers with abundant exoskeleton assistance experience have obvious advantages in speeding up the parameters exploration process and improving the assistant performance. However, there is no existing method that could utilize the human-exoskeleton locomotion interaction experience (HELIE) to assist naive wearers during the exploration process. In this work, we propose a novel preference-based human-exoskeleton locomotion interaction experience transfer (LIET) framework, which could speed up the exploration of human-preferred parameters and acquire more satisfying results for naive wearers via the HELIE acquired from knowledgeable wearers. In addition, based on the proposed LIET framework, we establish the mathematical expression of the HELIE transfer during exoskeleton assistance. This will promote the research that concerns utilizing HELIE for exoskeleton control parameters optimizations in the future. Finally, experiments demonstrate the proposed LIET framework could speed up the exploration process and acquire more satisfying optimized results for naive wearers.**

***Index Terms*— Preference-based optimization, lower-limb exoskeleton, Interaction Experience Transfer.**

I. INTRODUCTION

As a portable and intelligent wearable device, lower-limb assisted exoskeletons have shown their potential in walking assistance for human beings [1]–[3]. To maximize the comfort of wearers and the assistant performance of exoskeletons, researchers have devoted to designing methods to integrate human subjective and objective feedback (e.g. metabolic cost, human preference, EMGs, and joint moments) into control loops [1], [4]–[7], and have received exciting results.

Preference-based methods [8]–[12], which allow wearers to adjust the control parameters (e.g. joint moments and joint angles) of exoskeletons positively via their preferences and feelings [13]–[16], have become a kind of highly anticipated and promising optimization methods in recent years. Human subjective preference reflects not only their subjective perception of the nervous system but also the fuzzy perception of energy cost [17], [18]. By utilizing human preference, it is potentially possible to further enhance the role of human beings in the control loops.

Many works have indicated that compared with knowledgeable wearers (wearers with abundant human-exoskeleton locomotion interaction experience (HELIE)), naive wearers (without any HELIE) have obvious disadvantages in utilizing preference-based methods to explore better control parameters [11]. HELIE could provide posterior knowledge and enhance the wearers' recognition and comprehension of the optimized parameters. It has a significant impact during the optimization process of preference-based methods. Without HELIE, naive wearers are usually more confused, directionless, and cautious during the process of optimization, which will lead to more exploring attempts and even the missing of better parameters. However, in existing preference-based methods, HELIE has been rarely utilized for the optimization of exoskeleton control. Therefore, it is valuable to build a method to help naive wearers utilize the HELIE from knowledgeable wearers for promoting the exploration of preferred parameters, which could be called HELIE transfer.

Unlike the existing preference-based optimization methods, which are devoted to exploring better parameters in all possible domains to find a global optimum or establish a global preference landscape for some specific wearers [9], [10], HELIE transfer looks forward to utilizing the posterior knowledge from knowledgeable wearers to avoid pointless searching. Therefore, HELIE transfer aims to estimate the exploration process of knowledgeable wearers according to finite historical explorations of local preferences but not estimating the global preference landscapes. How to learn the relationship between the preferences and exploration process of wearers according to the demonstration samples from knowledgeable wearers is the key to HELIE transfer.

According to the analysis above, we propose a novel optimization framework called locomotion interaction experience transfer (LIET), as shown in Fig. 1. By utilizing the HELIE of knowledgeable wearers, the framework could guide the explorations of naive wearers according to their every exploration and selection during the optimization process. Experiments demonstrate the proposed framework could successfully transfer the HELIE of knowledgeable wearers to the naive wearers during the optimization process. As a result, naive wearers could avoid many unnecessary explorations and require better parametric results quickly.

*This work was supported by the National Outstanding Youth Science Fund Project of National Natural Science Foundation of China under Grant 52025054, the National Natural Science Foundation of China (NSFC) (No. 52105016), and in part by the Major Research Plan of the National Natural Science Foundation of China under Grant 92048301. *(Corresponding author: Yanhe Zhu.)*

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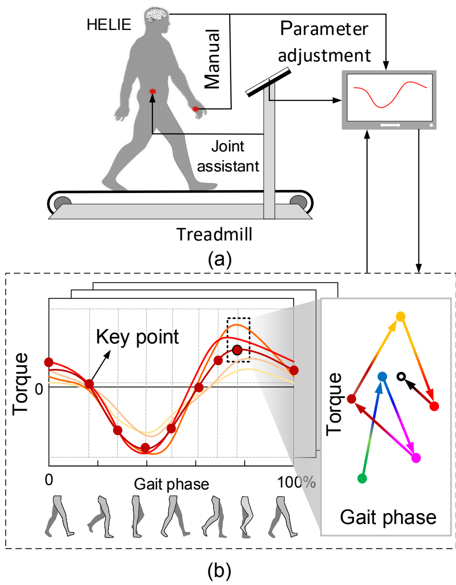

Fig. 1. The proposed LIET framework. (a) Wearers could adjust the joint moments shown on the touch screen based on their preference. (b) Optimization process of the joint moment parameters. The gait percentage and moment values corresponding to each key point could be cyclically adjusted according to the wearers' preference under the LIET framework. The zoomed-in image displays the adjustment process of the key points.

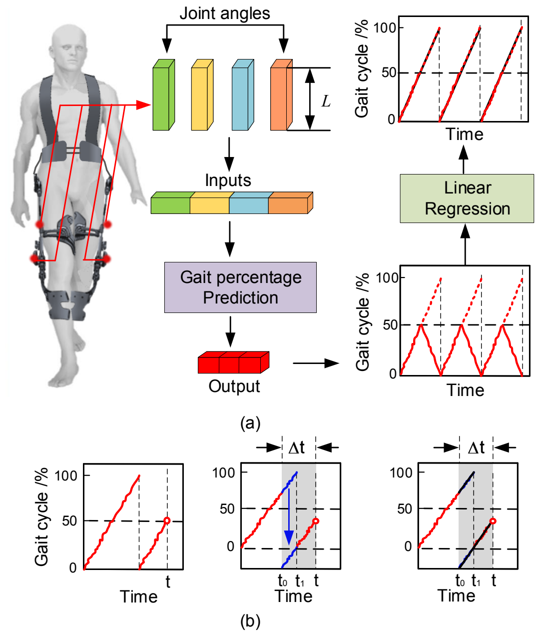

Fig. 2. The Method of Gait Percentage Predict. (a) The gait prediction process. Where L is the length of time. The joint angle data include hip and knee joint angles in the sagittal plane. (b) The operating principle of the linear regression model (LRM).

II. THE LIET FRAMEWORK

A. Human-Exoskeleton Locomotion Interaction Experience (HELIE)

In general, human preference is a subjective measure that can serve as an assessment of "goodness", or reflect the ordering of alternatives based on their relative utility [19]. The preference for control parameters of the wearers can reflect their subjective evaluation of the comfort and assistive performance of the exoskeleton.

In fact, human preference for exoskeleton controllers is growable rather than constant [19]. In most existing preference-based methods, wearers are allowed to traverse the whole landscape, randomly explore, or just choose the algorithm-provided parameters for the "goodness" [11]. Experiment results show that with the continuous exploration of exoskeleton control parameters, the wearers could gradually understand the influence of the parameters on comfort and assistance performance, and could even learn how to adjust their gait actively for a better assistance experience [11]. Research has confirmed that the HELIE can help the wearers explore the "goodness" more precisely and faster [19]. However, under these existing frameworks, HELIE has never been utilized to assist the wearers in control parameters explorations.

B. Preparation Work for HELIE Transfer

1) Gait Percent Prediction: Learning-based joint moment curve optimization methods like [20]–[22] usually apply optimized joint moments periodically according to the percent of gait cycles [22], thus requiring an estimator of the gait percent. An unstable estimator will lead to the fluctuation of joint moments and disturb the optimization [23]. It is the basis of the proposed LIET framework, thus is introduced in this section. In this work, we achieve the estimation of human gait percentages via a gait prediction model.

As shown in Fig. 2(a), the gait prediction model is a multi-layer neural network. The input and output size of the model is 800 (number of joints $\times$ time sequence) and 3. The model has two LSTM hidden layers with the sizes of 256 and 32, respectively. The input data is the sequential human joint angles and the output data represents the predicted gait percentage.

When the gait percentage turns to 0 from 100% as a new cycle comes, there will be a mutation. This puts forward higher requirements for the training of the model. To avoid the mutation, we split the one-dimensional gait percentage into two dimensions. The first dimension represents whether the gait percentage belongs to the first half gait cycle ($0-50\%$). The second dimension is calculated as equation (1):

$$X = \begin{cases} x, & 0 \leq x < 50\% \\ 1-x, & 50 \leq x < 100\% \end{cases} \tag{1}$$

Where x is the gait percentage, X is the second dimension of the output. In this way, the mutations of the gait percentages during walking could be avoided, as shown in Fig. 2(a). For security, the third dimension of the output represents whether the wearer is during normal walking.

The training data is collected on a treadmill and labeled with gait percentages manually. The treadmill speeds cover the main speed range of human walking (from 3 to 6 km/h). The negative samples mainly include squatting, random leg swings, and some other atypical lower limb movements.

There are usually inevitable deviations between the outputs of artificial neural networks and ground truth, which will finally lead to the fluctuations of the joint moment and influence the wearers' selection of their preference. To avoid this problem, we design a linear regression model (LRM) to smooth the gait percentage curve, as shown in Fig. 2(b). The LRM could calculate the average gradient of the predicted gait percentage curve in the past period (Δt) and eliminate mutations of the predicted results according to equation (2):

$$\hat{x} = \overline{k}(t - t_1) \tag{2}$$

Where $\hat{x}$ is the final estimated value of the gait percentage, $\overline{k}$ is the average gradient calculated by the least square method during the sliding time window Δt.

2) Control Parameters Optimization Process Samples Obtained from Knowledgeable Wearers: In the proposed framework, the wearers could optimize the joint moment curves by adjusting the key points (including the peak points, zero points, extreme points, and some user-defined key points) on the curve manually, and then the moment curve is produced via a spline. During this process, the checkpoints and the final optimized results of the knowledgeable wearers are recorded together. These data could provide significant posterior knowledge for naive wearers.

The moment curve samples collection is set and completed on a treadmill. During the experiments, participants can adjust the curve displayed on a touch screen manually according to their preference. Before experiments, the physical meaning of each point on the curve will be notified to the participants in advance.

C. Locomotion Interaction Experience Transfer (LIET) from Knowledgeable Participants to Naive Users

1) The Mathematic Expression of the Skill Transfer under Exoskeleton Assistance: Establishing a mathematical representation of human preference transfer is necessary to transfer the HELIE. In many existing works, human preference is represented as a utility function to describe the landscapes of preference [8]–[10], [24]. However, HELIE transfer looks forward to estimating the exploration process of knowledgeable wearers according to finite explorations of local preferences but not the global preference landscapes. This is the estimation of a hinged exploration but not establishing a global assessment. Therefore, the process of exploration and selection must be contained in the mathematical representation.

The process of human decision when facing different parameters could be described as Fig. 3(a). Where the points from A to E represent the combinations of control parameters, the numbered arrows *1* to *5* represent the order of explorations, and the colors from red to $green$ represent whether the exploration is successful. Color $blue$(point D) means there is not a clear priority between the explored parameter combination (point D) and the last one (point B).

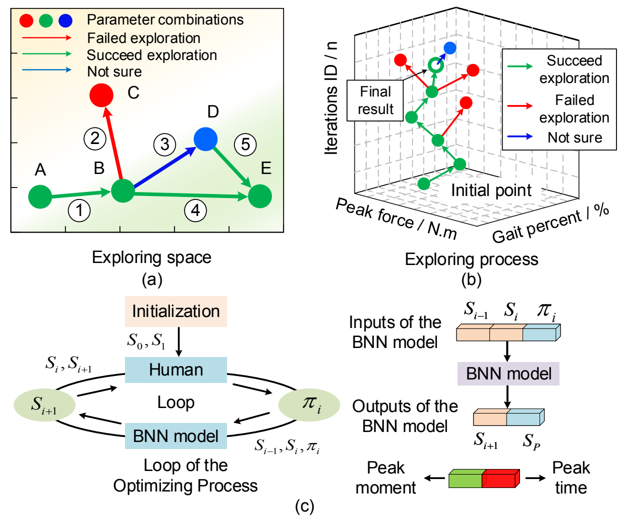

Fig. 3. Mathematical representation of HELIE transfer. (a) Exploration process diagram. The letters represent combinations of control parameters. The numbered arrows represent the order and direction of explorations. The colors represent the correctness of each exploration. The red and green lines indicate the failed and the successful explorations compared to the previous control parameters. The blue line indicates that the wearer could not distinguish which is better. (b) The exploration process in peak force and gait percent according to weraers' preference. The final result is represented by an open circle. (c) Model-based cyclic optimization process.

The whole process can be regarded as a *Markov process*. Every parameter combination could be regarded as a sequential state in the *Markov chain*. Therefore, the preference-based optimization process can be illustrated as equation (3),

$$P(\pi_A|S_A S_B) = P(S_P = A|S_i = A, S_{i-1} = B) \tag{3}$$

$$S_i = (t_i, F_i) \tag{4}$$

where S_A and S_B represent the optimized parameter combinations A and B are explored at times i and $i-1$ respectively, π_A denotes the wearer prefer the parameter combination A when both A and B are considered. t_i and F_i represent the gait percentages and joint moments of the key points in parameter combination S_i. According to equation (3), the human preference can be represented as the probability of $P(\pi_A|S_A S_B)$, which means the wearer prefers parameter A between parameter A and B.

The LIET framework proposes the historical decision and the exploration process of knowledgeable wearers could be the posterior knowledge of naive wearers. This relationship could be described as:

$$P = P(S_C|\pi_B S_A S_B) \tag{5}$$

where the result P represents the probability that the wearer explores C when the wearer preferred B than A. The probability P describes the HELIE that could be transferred from knowledgeable wearers to naive wearers.

2) The Skill Transfer Based on the Bayesian Optimization Method: As analyzed in section II-A, transferring the HELIE from knowledgeable wearers to naive wearers could speed up the optimization process of the latter and improve the performance of the optimized parameters. The advantages of owning the HELIE are mainly reflected in the success rate in exploring new parameters. A higher success rate signifies fewer exploration steps and acquiring better parameters. According to equations (3) and (5), the transferring process is exactly the process of estimating the exploration S_{i+1}. Therefore, the problem can be described as estimating the expectations of the parameters explored by knowledgeable wearers, which is represented as:

$$E = \sum_{S_{i+1} \in D} P(S_{i+1} | \pi_i S_i S_{i-1} \pi_{i-1} S_{i-1} S_{i-2} ...) S_{i+1} \quad (6)$$

where E is the expectation of the next explored parameters S_{i+1}, D is the feasible domain of S_{i+1}.

According to the fundamentals of machine learning, equation (6) could be regarded as the regression problem for S_{i+1} based on the exploration and decision history $[S_i S_{i-1} \pi_{i-1} S_{i-1} S_{i-2}, ...]$. There are some existing methods for the time sequence data. Compared with other methods, the Bayesian optimization method has been widely used in metabolic optimization of lower-limb assistance because of its efficiency and no derivative required feature [25]–[29]. Furthermore, Bayesian networks usually have better performance in learning the causality of data distribution based on the posterior distribution of training data. Therefore, in this work, we establish a BNN to estimate S_{i+1}.

The model is built based on an existing universal probabilistic programming library [30] and its Bayesian regression optimizer. Utilizing this library, we can easily establish a neural network model and optimize the network parameters by Bayesian optimization theory. Due to the difficulty of collecting the explorations from knowledgeable wearers, the history data just chooses one optimization round as $\pi_i S_i S_{i-1}$. Finally, the proposed BNN model has three linear layers (including a hidden layer with a size of 4), the input size is 6, and the output size is 4. The input vector of the BNN model is reshaped from the vector $\pi_i S_i S_{i-1}$ (3×2), and the outputs of the model include the next explored parameter set S_{i+1} and the predicted final optimized result S_P (2×2). Thus,

$$S_P, S_{i+1} = f_B(\pi_i, S_i, S_{i-1}) \quad (7)$$

where f_B is the BNN model. The predicted next explored parameter combination is estimated as:

$$\hat{S}_{i+1} = (1 - f) S_{i+1} + f S_P \quad (8)$$

$$f \in (0, 1] \quad (9)$$

where f represents the weight of S_{i+1} and S_P. f is a pre-set hyperparameter, a larger value f will speed up the optimization process and reduce the exploration times, but may also lead to a wrong local optimum due to the excessive reliance on individual historical data samples. As shown in Fig. 3(c), the framework is described as follow:

- The wearer is promoted to give a preference between a set of randomly initialized parameters (A) and a set of active exploratory parameters (B). In this way, the first input sequence $[\pi_A, S_A, S_B]$ is established.
- According to $[\pi_A, S_A, S_B]$, the well-trained BNN will provide a set of new parameters for the participants to continue the optimization process.

For the naive participants, the first choice π_A might be unreliable. To avoid a wrong choice misleads the BNN model to identifying the wearers' preferences and leads to a wrong local optimum, after each parameter generation by the BNN model, the participants were prompted to make their own exploration according to their feelings. These exploratory steps, proposed by the wearer himself, will continually revise the BNN model's understanding of the wearer's preferences, which will ensure that the optimization results converge to the wearer's real preferences.

III. EXPERIMENTS

The experiments are designed to evaluate the performance of the proposed LIET framework, focussing on whether the framework could speed up the optimization process and explore more satisfying control parameters. To verify these conclusions, we design two sets of experiments, and we will narrate the details of these experiments in this section.

A. Experimental Platform

The experiments utilize a lightweight lower-limb exoskeleton system, which can provide the maximum moment of 12 N.m at hip joints, as shown in Fig. 4. Seven healthy knowledgeable adults and six healthy naive adults participated in the experiments. First, they were informed about the research procedure. Then, each participant signed a written consent form approved by the Institutional Review Board of the Harbin Institute of Technology.

B. Samples Collection of the Knowledgeable Wearers' Preference

This set of experiments is designed to collect the samples from the knowledgeable wearers. During the experiments,

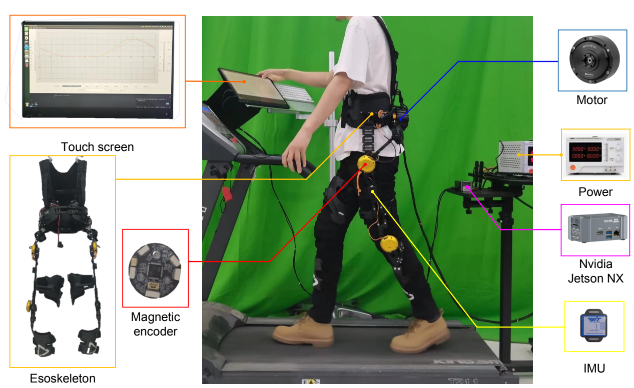

Fig. 4. Experimental Plattform. The main information of the exoskeleton is listed as follows: gear motor (AK80-9, Cubemars, China), inertial measurement unit (IMU) (WT61C, WIT, China), self-designed encoder and CAN master board, and embedded computer (Jetson NX, Nvidia, USA).

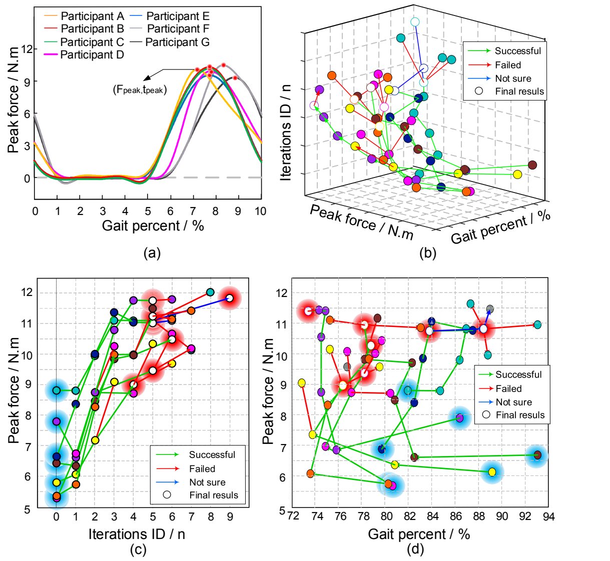

Fig. 5. Samples obtained from knowledgeable wearers. (a) Optimized moment curve results. (b) The exploration process of the knowledgeable participants. (c) Distribution of starting and ending points at the dimensionalities of peak moments and interaction times. (d) Distribution of starting and ending points at the dimensionalities of peak moments and gait percentages.

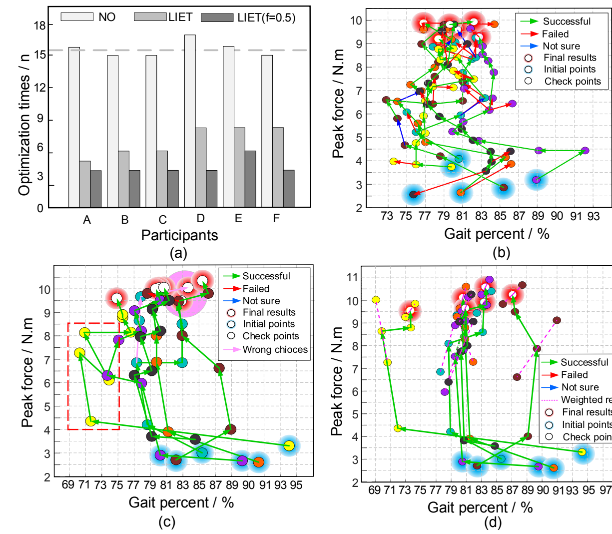

Fig. 6. Experimental verification of the proposed LIET. (a) Comparison of optimization times. Light gray indicates the number of optimizations without LIET. Grey indicates the number of optimizations with the help of LIET when $f = 0$. Dark gray indicates the number of optimizations with the help of LIET when $f = 0.5$. (b) Detailed optimization process without LIET. The blue and red circles represent the initial points and the final results of the exploration, respectively. Different colors of points represent different participants. The red, green, and blue lines represent erroneous exploration, correct exploration, and the results that are difficult to select, respectively. (c) Detailed optimization process with LIET when $f = 0$. The red dotted box area indicates some selection errors and failed explorations. The pink lines represent the convergence path starting from the artificially designated erroneous node. The pink path and the corresponding normal path converge in the pink area. (d) Detailed optimization process with LIET when $f = 0.5$. The dashed line represents the weighted result for S_{i+1} and S_P.

seven knowledgeable participants wore the lower-limb exoskeleton and walked on a treadmill with a speed of 4 km/h. They were allowed to tune the hip joint moment curves as they willed within acceptable limits of the exoskeleton. To simplify experiment complexity and reduce uncertainty, in this experiment, only the peak time and the peak moment of the joint curves during the hip joint lifting phases were collected. For every pair of peak times and the peak moments, the participants could adjust the rising time and the ending time of the curves to fit the change of the peak times and the peak moments until acquiring the best feelings under the corresponding peak time and the peak moment. The adjustment of the rising time and the ending time were not accumulated to the total iterations. The results are shown in Fig. 5(a).

The optimized joint moment curves are shown in Fig. 5(a). The relation between the optimized peak time, peak moments, and tuning times during the process are shown in Fig. 5(b), a green, red, and blue line with arrows represents a successful exploration, an unsatisfactory exploration, and an indistinguishable result, respectively. The points with different colors represent different participants. As shown in Figs. 5(c), and (d), the peak torque explored by the wearer generally presents an upward trend. The first few explorations of the participants are directional and almost always successful explorations, which highlights the contributions of their experience, recognition, and skills during the optimization process. In addition, although the initial points (the point with blue makers) are relatively random, the adjustment directions and the final results (the point with red makers) show a certain regularity.

C. Verification of HELIE Transfer Towards Naive Wearers

This set of experiments is designed to verify the skill transfer from knowledgeable participants to naive wearers participants Based on the collected preference samples, the BNN could learn the expectations of the next explored parameters, which could be regarded as the manifestation of the transferred HELIE.

Six naive participants took part in this experiment. Each participant completed the parameter optimization according to their preference independently under three conditions: without the LIET framework, under the LIET framework with a f of 0, and the LIET framework with a f of 0.5. There was a one-week time interval between every two conditions for each participant to fade the optimized results and feelings about the exoskeleton assistance from their memories. Furthermore, during this process, the coordinate value is hidden from the participants to avoid the participants keeping the optimized parameters in mind. The orders of three optimization conditions for each participant were random. This would eliminate the interference of each participant's experience in the earlier optimization on the influence of the later optimization on the result analysis. The end condition of the optimization process is defined as when five successive failed occur, which means the participants could not find better parameters. These five successive failed were not counted in the total loop. The exploration processes of three conditions are shown in Fig. 6(b).

Finally, to compare the performance of the independent optimized results of the naive participants and the results optimized utilizing the proposed method, each participant was promoted to select the most satisfying result between the independent result, the results optimized utilizing the proposed method with the f of 0 and 0.5, respectively.

A comparison of the results revealed important information that is discussed next.

D. Analysis and Discussion

According to the results, there are several important conclusions to be highlighted:

- Compared with knowledgeable participants, the explorations of the naive participants are more directionless, have smaller step sizes, contain many repetitions explorations and wrong choices, and need more optimizing loops, as shown in Fig. 5(b), (d) and Fig. 6(b). This reflects the directionless of the exploration and indeterminacy of the preference of the naive participants and highlights the contributions of the HELIE.
- The naive participants usually stop early before exploring larger peak moments, which might be due to their cautious and conservative attitudes toward higher joint moments. This will hinder them from reaching a better assistance performance.
- Compared with their independent search results, the proposed method greatly reduces the number of optimizations (from 16, 15, 15, 17, 16, 15 to 5, 6, 6, 8, 8, 8). By introducing the predicted values S_P, the extent of speed increase could be more obvious (4, 4, 4, 4, 6, 4), as shown in Fig. 6(a). This verifies the performance of the proposed framework in speeding up the preference-based optimization strategy.
- The peak moments optimized utilizing the proposed framework are usually larger than the independent optimized results of the naive participants (from 9.52 N.m, 9.60 N.m, 9.83 N.m, 9.21 N.m, 9.98 N.m, and 9.82 N.m to 10.04 N.m, 10.34 N.m, 10.05 N.m, 9.59 N.m, 10.00 N.m, 10.06 N.m when $f = 0$, and to 10.26 N.m, 10.56 N.m, 10.13 N.m, 9.56 N.m, 10.59 N.m, 9.67 N.m when $f = 0.5$), and most of the naive participants prefer the LIET proposals (One participant is not clear about the best parameters between the independent optimized results and the LIET-advised result when $f = 0.5$, two chose the LIET-advised result when $f = 0$, and three chose the LIET-advised result when $f = 0.5$). This demonstrates the proposed framework could help the preference-based methods improve the optimization performance.
- There are some wrong selections of preferred parameters and failed explorations during the process of optimizations utilizing the proposed framework, which is discovered according to the distance between the selected point and the final results, as shown in 6(c)(the checkpoints in the red dotted box area). These will mislead the well-trained model of the participant's preference. However, the proposed framework could still converge to satisfactory results finally. To verify the precision of the result when wrong selections and failed explorations occur, we artificially changed the selections and restarted at the wrong node. The final result was close to the old one, this highlights the robustness of the proposed framework, as shown in Fig. 6(c)(the pink line and the two results in the pink area).

In conclusion, the experiments verify the proposed framework could successfully transfer the experience and skills of knowledgeable wearers to the optimization process of naive wearers via preference-based methods. This is specific in speeding up the optimization process and improving the performance of the final optimized results.

IV. Discussion

Due to the deficiency of HELIE samples, there are some unconscionable selections and exploration during the optimization process of naive wearers, as shown in Figs. 6(c). These will mislead the BNN model in the proposed LIET framework. Although the optimization process still converges to a correct result, these misleadings will increase the optimization loop. The main reason for this issue is that when collecting the preference samples from knowledgeable wearers, the HELIE helps knowledgeable wearers reduce unconscionable selections and explorations thus leading to the deficiency of these unconscionable samples in the training set of the BNN. In future work, we will focus on this problem and try more types and structures to improve the performance of the existing BNN model.

Although we only optimized one key point in the experiments to verify the proposed LIET framework, the results can also verify the performance of the LIET framework. In fact, the LIET allows users to estimate more parameters, and this part will also be expanded in future work.

V. Conclusion

The main contributions of this work are summarized as follows:

First, this work proposes a significant scientific problem of HELIE transfer and highlights the importance and roles of HELIE, which is rarely paid attention to before in most preference-based optimization methods.

Second, based on the proposed LIET framework, we establish the mathematical expression of the HELIE transfer during exoskeleton assistance. This will bring great convenience and promote the research that focuses on utilizing HELIE for exoskeleton control parameters optimizations in the future.

Finally, the proposed LIET framework can greatly speed up the exploration process for preferred control parameters (the joint moment and corresponding gait percentages of every key point on optimized joint moment curves) and explore more satisfying control parameters for naive wearers. It will improve the practicability and promote the promotion of preference-based optimization methods for exoskeletons.

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