2024 6th International Conference on Data-driven Optimization of Complex Systems (DOCS) | 979-8-3503-7784-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/DOCS63458.2024.10704430

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Force Calibration of Soft-sensing Unit for Flexible Exoskeleton

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***Abstract*—Soft sensors are increasingly used in wearable devices as well as soft robotics. This paper introduces a novel, lightweight soft-sensing unit and a new data collection method, aimed at enabling the implementation of soft sensors in robotics. These advancements are designed to replace traditional sensors, providing precise data capture and comfortable wearing experience. Through machine learning, soft stretchable sensors originally used for displacement detection have been endowed with the capability to precisely detect tension. The research first involves six participants and two scenarios (manual assistance, motor assistance on treadmill walking), providing high-quality data with different variability for model training. The results demonstrate that the Gated Recurrent Unit (GRU) model outperforms others under comparison in this study, achieving a root mean square error of 2.92 N. Transfer learning is then used to improve the performance of our model under another condition (manual assistance on level ground walking), which achieves 271% improvement in R^2 and maintains consistent performance with data collected from another participant. Our flexible exoskeleton has been tried by a new subject and achieved comfortable assistance without the use of a load cell. Our unit, along with its calibration method presented in this paper, holds great promise for the actual deployment of soft sensors in soft robotics.**

***Index Terms*—Soft sensor, Recurrent neural networks, Transfer learning, Flexible exoskeleton**

I. Introduction

Soft stretchable sensors are receiving growing attention and are now being extensively implemented in wearable devices [1]–[4], such as smart sleeves [5], serving as alternatives to traditional rigid inertial measurement units (IMUs). Furthermore, their application to monitor real-time stress and strain is also expanding [6]. However, soft sensors often exhibit hysteresis and are sensitive to temperature and humidity [7]. In addition, they are affected by high manufacturing tolerances and experience signal drift from long-term usage [3], which limits their applications.

This work was supported in part by Key Research and Development project of Zhejiang Province [No.2024C03040], in part by the Zhejiang Public Welfare Project [No.304LTGY23H170002], in part by the Ningbo Public Welfare Project [No. 2023S111]

Luying Feng and Lianghong Gui equal contributions

Machine learning techniques, which have a strong ability to address non-linear challenges [8], have significantly advanced the use of soft sensors across various domains. Han *et al*. implemented a hierarchical recurrent sensing network, which can estimate the magnitude and the location of a contact pressure on the soft sensor simultaneously [9]. Transfer learning has emerged as a powerful strategy to enhance the capabilities of soft sensors, enabling them to adapt to varying environmental conditions and address challenges such as sensor wear and drift. This approach leverages pre-trained models, adapting them to new but related tasks, which mitigates the need for extensive recalibration and extends the operational lifespan of the sensors. Kim *et al*. experimentally validated Optimal Transportation Transfer Learning using actual soft sensors, demonstrating its effectiveness in maintaining sensor accuracy and reliability over time [3].

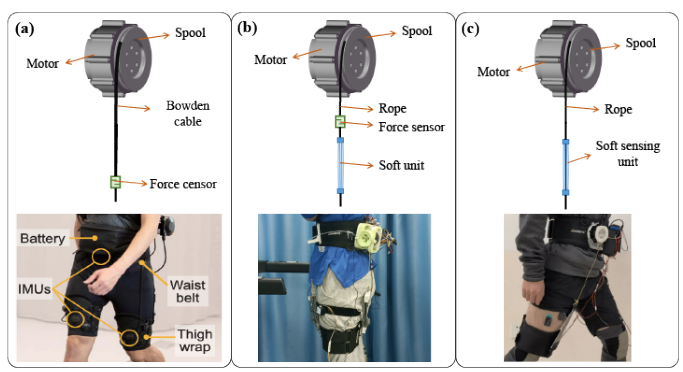

Fig. 1. Diagrams and physical examples of Flexible Exoskeletons. (a) Diagram and physical example of a Bowden cable driven flexible exoskeleton [10], (b) Diagram and physical example of SSEA flexible exoskeleton, (c) Diagram and physical example of a novel SSEA flexible exoskeleton without load cell (based on soft-sensing unit).

In our previous study [11], we proposed a soft series elastic actuator (SSEA), as shown in figure 1 (b). Comparing to the research of Conor J. Walsh's group [10] shown in figure 1 (a), our SSEA exhibits physical compliance for exoskeleton. In our another previous study [12], based on above SSEA, we developed a novel sensing-actuation integrated unit for elastic tension transmission and force estimation, as shown in figure 1 (c). Then we developed a data collection platform that uses motors to stretch sensors according to sine curves of different frequencies and amplitudes for data collection. Both long short-term memory (LSTM) and Informer models we selected demonstrated good performance. While LSTM may be slightly inferior in terms of accuracy, it compensates with faster computational speed. Despite these advancements, our previous study identified several limitations:

- The data was collected on a simulation test platform. Despite the addition of random factors, the motor stretched the unit following a sine function-based curve.
- The unit incorporates clamps, which render it somewhat inflexible, as well as noticeably thick and heavy.

In this study, we redesigned the soft-sensing unit to enhance its flexibility, and to make it lighter and thinner. The data collection method has also been improved, making the collected data more random and realistic. Data was collected in three scenarios. In the first scenario, five participants independently pulled the soft-sensing unit attached to their thigh while walking on a treadmill at various speeds to achieve self-assistance. In the second scenario, five participants wore an exoskeleton equipped with a soft-sensing unit on a treadmill to conduct assisted movement experiments, with the exoskeleton providing the assistance. In the third scenario, two participants wore thigh bands equipped with a soft-sensing unit while walking on level ground at self-perceived slow, medium, and fast paces to achieve self-assistance. To our best knowledge, this is the first study to employ soft sensors as a force sensor in exoskeleton assistance experiments for data collection and this research is significant as it advances the application of soft sensors in exoskeletons, enhancing their functionality and usability.

II. System design

Building on our previous foundation [12], this study introduces several significant improvements. As shown in figure 2 (a, c), the original plastic elastic band has been replaced with a 90-pound textile elastic band, and the previous paper-cut shielding layer has been upgraded to a stretchable conductive fabric. Additionally, the clamping method used for fixing the unit has been replaced by sewing, reducing the weight of the soft sensing units. When stretched to 150% of its original length, the unit can provide a pulling force greater than 90N, which can offer approximately up to 14Nm of equivalent hip flexion/extension torque, which is approximately 30% of the human walking torque. So, the redesigned unit is reasonable and meeting the necessary assistance requirements. Furthermore, this study upgraded the previous capacitance reading device by adding a shield cover, as shown in figure 2 (b, d).

The overall diagram of the exoskeleton system in this study is shown in figure 3. The shoulder straps effectively prevent the waist belt from sagging during walking and reduce pressure on the anterior superior iliac spine. The connection buckles at the thigh straps facilitate easy assembly and disassembly of

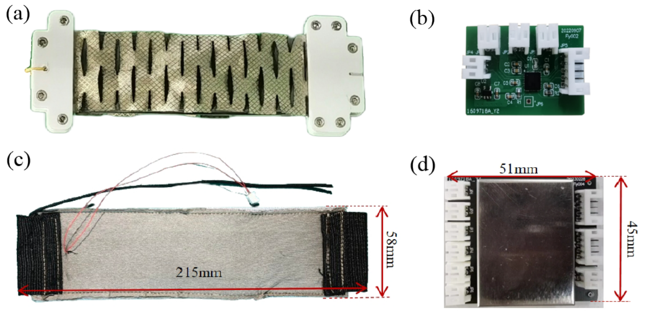

Fig. 2. Redesign of soft-sensing unit and capactive reading device. (a) old soft-sensing unit, (b) old capactive reading device, (c) updated soft-sensing unit, (d) updated capactive reading device.

the soft-sensing units. Reinforcement ribs at the thigh straps, made of two tough plastic pieces sewn inside the thigh bands, effectively prevent the soft thigh straps from lifting due to stretching during assistance while maintaining flexibility. The yellow box indicates the location of the force sensor. The force sensor is used in conjunction with flexible sensors to synchronously collect force data, which aids in model training for later stages. The motor is fixed to the soft waist belt via a motor mount. Due to the softness of the belt, the bolt heads used for mounting the motor are recessed, ensuring comfort during wear. The motor shaft is connected to a spool, driving the flexible ropes through fixed pulleys to stretch the thighs. The structural design of the four fixed pulleys ensures alignment with the motor pulleys and reduces friction during force transmission. The smart knee pads can predict knee joint angles with an average MAE of 4.910° and hip joint moments with an average MAE of 0.085 Nm/kg.

This newly designed exoskeleton system weighs only 2.3 kg (including batteries and smart knee pads), demonstrating a significant weight advantage compared to other unilateral flexible exoskeletons. To control robots, various methods are employed in different research [13], including position control, impedance control, hybrid control [14], force control, etc. In addition, assistance strategies are usually planned through two types of signals: joint angles [15] or joint moments [16]. Here, we use force control and plan assistance through real-time hip joint moment.

III. Data Collection and Prepossessing

A. Data Collection

This study involved five participants in Scenario 1 and five participants in Scenario 2 for data collection, as depicted in figure 3. Additionally, two participants (one from the initial group and one new participant) were involved in another scenario for transfer learning and model testing. For the final test, a new participant wore the SSEA flexible exoskeleton without a load cell and conducted assisted movement experiments on a treadmill. Participant information is shown in table 1.

In the first scenario, five participants (N01-N05) wore thigh bands equipped with a soft-sensing unit while walking on a

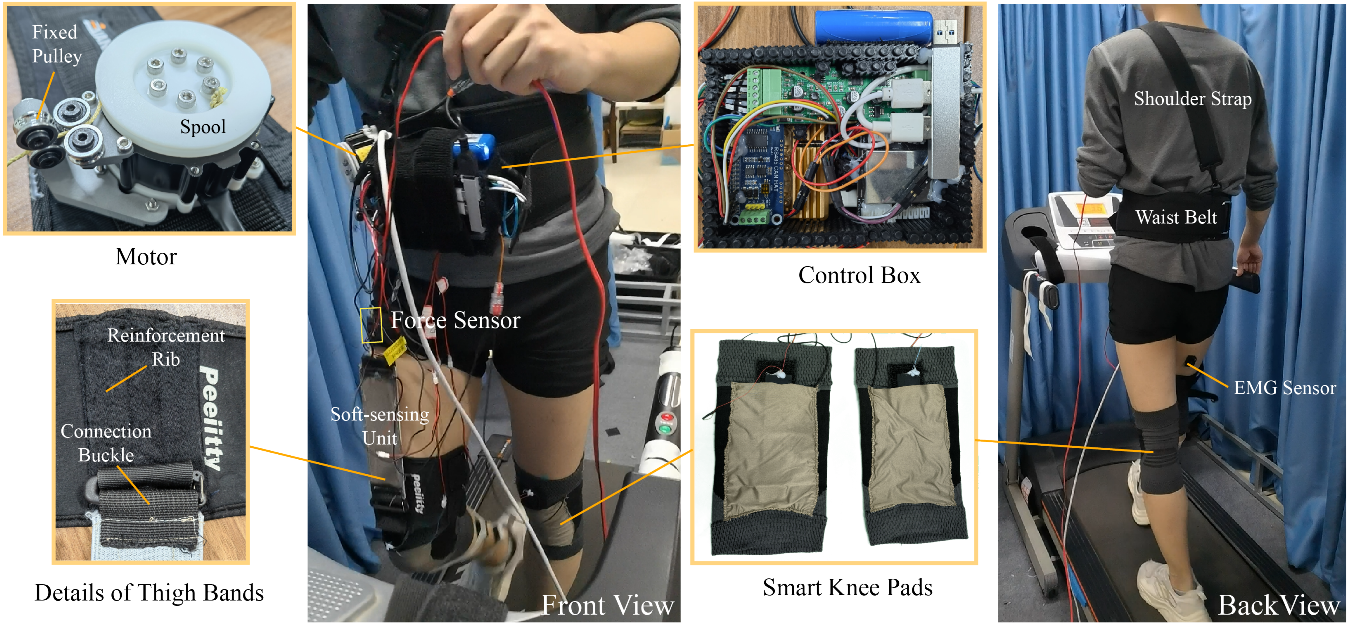

Fig. 3. System diagram.

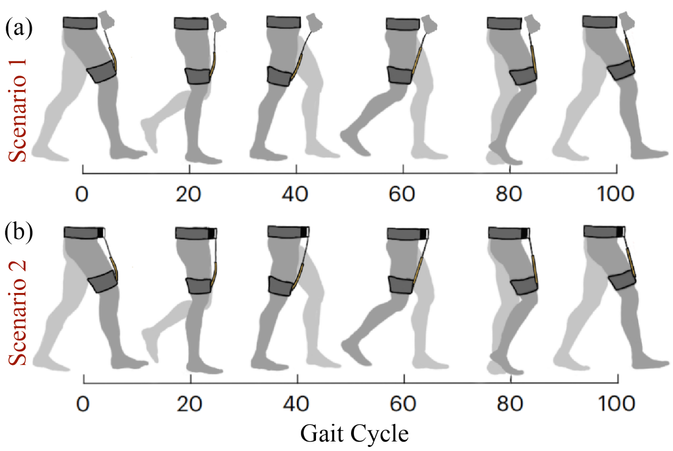

Fig. 4. Data collection scenarios. (a) Participants independently pulled a soft-sensing unit attached to their thigh, (b) Participants wore an exoskeleton equipped with a soft-sensing unit, with the exoskeleton providing assistance.

TABLE I
SUBJECT INFORMATION

No.	Age	Gender	Height (cm)	Weight (kg)
N01	24	Male	178	62
N02	23	Male	180	66
N03	22	Male	168	65
N04	28	Male	172	75
N05	24	Female	152	49
N06	35	Male	169	75
N07	24	Male	175	72
N08	23	Male	173	65

treadmill at speeds of 0.5, 1.0, 1.5 m/s, and a self-selected speed. During the walking process, participants were able to pull on the other end of the soft-sensing unit at will, providing self-assistance in walking. All data for Scenario 1 was collected on December 22, 2023. In the second scenario, five participants (N01-N04, N06) wore the exoskeleton shown in figure 4 and walked freely on a treadmill. Data from N01 and N02 was collected on January 23, 2024, while data from N03, N04, and N06 was collected on January 30, 2024. Due to viscoelastic effects, sensor will experience drift over time. Therefore, all collected capacitance data are subtracted by the initial value when the sensor is not stretched. The data from the force sensor and the soft-sensing unit were collected at a frequency of 100 Hz. All collected data included start-stop information, and the second scenario also encompassed data from partial debugging sessions.

B. Data Prepossessing

After data collection, rows containing NaN values were removed, followed by the exclusion of the first and last two data points from each data file. Outliers were then eliminated. Prior to training, the mean and variance of the training set were calculated, and all data were standardized.

To enhance the model's generalization ability, this study employed four-fold cross-validation as shown in figure 5. The data from participants N01 to N04 were used as the training set, with data from one participant selected as the validation set in each fold. The data from participants N05 and N06 were used as the test set. The data from both scenarios will be combined for training. We first used the LSTM model to observe the impact of different lengths of feature sequences on the validation set error, with the mean squared error (MSE) and the average inference time shown in figure 6. To balance

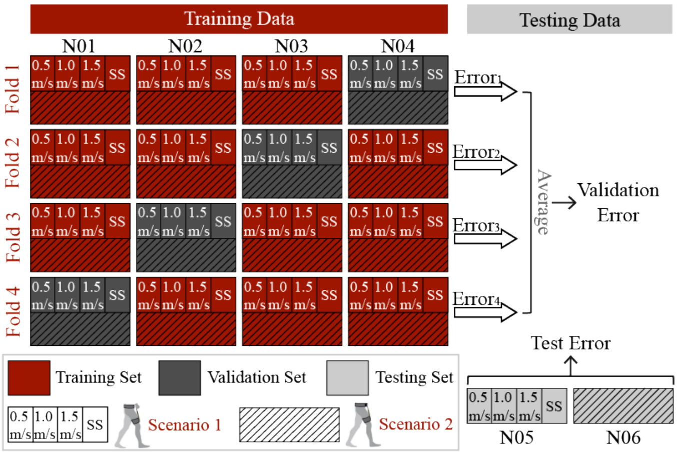

Fig. 5. Data partitioning scheme.

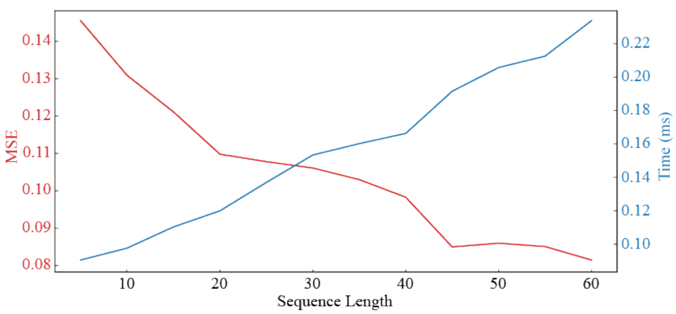

Fig. 6. Results of MSE errors on validation set (before destandardization) and the average time on predicting via different sequence length.

error and time consumption, a sequence length of 45 (i.e., 0.45 seconds) was selected a feature, with the force sensor data at the 45th time point used as the label.

IV. Results

A. Model Selection

In our previous research, we came to the following conclusions. The Informer model [17] performed better than the LSTM model but were computationally intensive and took more than twice as long on calculating [12]. Given that the model from this study is intended for use in a portable exoskeleton with an embedded system in future research, it is essential to minimize inference time while maintaining accuracy. Therefore, in this section, we will select the most suitable model for our time-related data from several basic regression models.

- Linear Regression (LR) is a basic and widely used statistical method for modeling the relationship between a dependent variable and one or more independent variables by fitting a linear equation to observed data.
- Recurrent Neural Networks (RNNs) are a class of artificial neural networks designed for sequential data processing. They feature connections that form directed cycles, which allow them to retain memory of previous inputs. This capability is particularly beneficial for applications such as time series analysis and natural language processing [18].
- LSTM is a type of RNN model first presented in [19], it can learn to identify important inputs, store them in a long-term state, and extract them when needed. Compared to the traditional RNN models, LSTM seems to be much more suitable for predicting long sequences. The LSTM model has been used in many related researches [20]–[22], solving the non-liner problems of soft sensors.
- GRU is another type of RNN architecture similar to LSTM but with a simpler structure. GRU use gating mechanisms to control the flow of information, which helps in learning long-term dependencies in sequences [23].

TABLE II
Estimation Results of Different Models

Models	MAE	RMSE	R^2
LR	2.7393	3.6112	0.8956
RNN	2.5582	3.3486	0.9103
LSTM	2.1256	2.9262	0.9315
GRU	2.1449	2.9227	0.9316

We trained the models on a PC equipped with a 13th Gen Intel (R) Core (TM) i9-13980HX 2.20 GHz CPU and an NVIDIA GeForce RTX 4070 laptop GPU. The grid search method was utilized to optimize the hyperparameters, and the models were subsequently evaluated on the test set. table 2 presents MAE, RMSE and R^2 of LR, RNN, LSTM and GRU, and figure 7 details the performance on certain part of test set. LR is used as a baseline model, providing a simple reference point to compare the performance of more complex models.

TABLE III
GRU Network Architecture

Layer index	Model	Parameters
1	GRU	Hidden:256, Dropout:0.4, return_sequences=True
2		Hidden:128,, Dropout:0.2, return_sequences=True
3		Hidden:64
4	DENSE	1

The results demonstrate that both the GRU and LSTM models outperform the others, with similar performance on the test set. Given the computational efficiency, we selected GRU as our final model (M1). The network architecture of the GRU is illustrated in table 3. The model processes data in batches of 1024 and in step size of 5. The initial learning rate was set at 0.001 and was adjusted to 0.9 times its original value if there was no decrease in validation set error for three consecutive epochs during training. The basic training consists of 100 epochs, with early stopping implemented if the validation set error does not decrease for 15 consecutive epochs, helping to prevent overfitting.

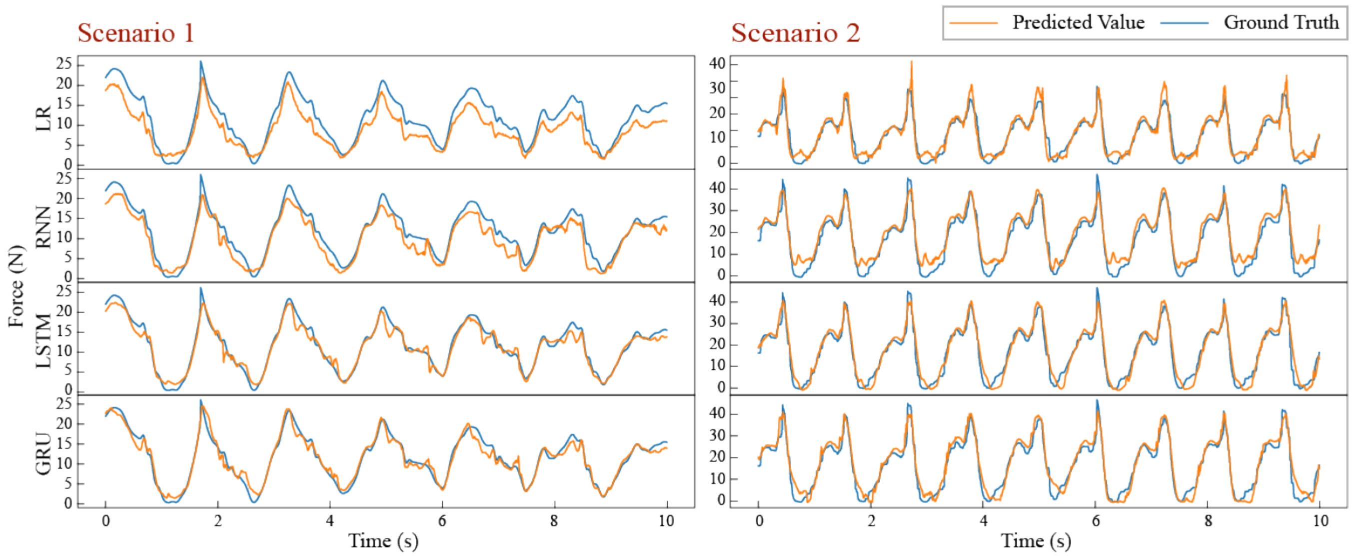

Fig. 7. Performance of different models on Scenarios 1 and Scenarios 2.

B. Transfer Learning

To verify the model's generalization ability, we applied it to data collected from Subject N03 in scenario 3: N03 wore thigh bands equipped with a soft-sensing unit while walking on level ground at self-perceived slow, medium, and fast paces for 2 minutes, respectively, two sets of data were collected. During the walking process, participant was able to pull on the other end of the soft-sensing unit at will, providing self-assistance in level ground walking (including turning). The data were collected on December 5, 2023, and unlike other collected data, it was not from the same day or the same scenario.

As illustrated in table 4, the model M1's error on N03's data increased dramatically. figure 8 (a) presents the performance of model (M1) before transfer learning, we find that the orange curve (performance of M1 on N03's data collected in scenario 3) generally follows the shape of the ground truth, yet discrepancies are evident, particularly in the force amplitude, which sometimes overshoots or undershoots the actual values. Different times and scenarios result in the collected data distribution being very inconsistent with the data previously used for training, especially since subjects in scenario 3 were willing to use greater force to pull the unit. Therefore, the upper end of the prediction results becomes flattened.

To further enhance the model's performance in real-world scenarios and mitigate the impact of drift, this study introduces transfer learning. Transfer learning is a powerful technique in machine learning that involves taking a model developed for one task and reusing it as a starting point for a different but related problem. This approach leverages pre-learned knowledge, which can lead to significant improvements in learning efficiency and prediction accuracy for the new task, especially when the available data is limited [24].

We used another set of the N03 data for transfer learning and again predicted the data of N03. Without altering the original model M1's architecture, we froze the parameters of the first layer and fine-tuned the remaining layers. The first 80% of the data was used as the training set, and the latter 20% served as the validation set. figure 8 (a) presents the performance of model (M2) after transfer learning, comparing it with the ground truth data over a period of 16 seconds. The red curve (after transfer learning) aligns closely with the ground truth, demonstrating significant improvements in accurately tracking oscillations and matching peak values more precisely than the orange curve, achieving 271% improvement in R^2.

TABLE IV
ESTIMATION RESULTS BEFORE AND AFTER TRANSFER LEARNING

Models	Data Source	MAE	RMSE	R^2
M1	N03, Scenario 3	12.8589	14.5352	0.2663
M2	N03, Scenario 3	1.2776	1.8036	0.9887
M2	N07, Scenario 3	1.3388	1.9241	0.9843

Data from Subject N07 (a totally new subject) in scenario 3 was also collected on December 5, 2023 and was used to test model M2 again. Performance22 illustrates the prediction results and figure 8 (b) presents the performance of M2. We can find that the model has well maintained its original performance, with only a 0.45% decrease in R^2.

V. Discussion and Conclusion

The primary objective of this research was to improve the functionality of the soft-sensing unit and utilize machine learning techniques to accurately estimate the tension derived from the sensor's capacitance data in scenarios that more closely mimic real-world conditions. This study successfully addresses several limitations identified in prior research, notably in the areas of the soft-sensing unit and data acquisition methods. The redesigned soft-sensing unit introduced in this research is innovative, and the data collection methodology employed is unprecedented in related studies, offering substantial reference

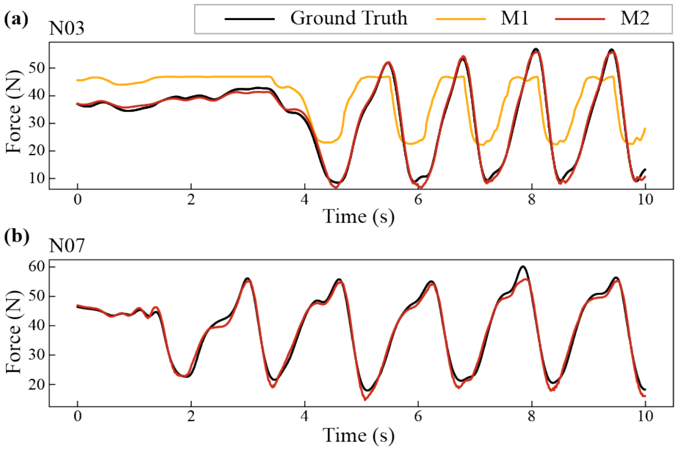

Fig. 8. Model Performance. (a) Force prediction performance before and after transfer learning on N03's data, (b) Force prediction performance after transfer learning on N07's data.

value for the integration of soft sensors in exoskeleton applications. For the final test, N08, a new participant, wore the SSEA flexible exoskeleton without the load cell and conducted assisted movement experiments on treadmill, with the force required for closed-loop force tracking control provided solely through the soft-sensing unit. The related trial video can be found in the appendix, which also includes demonstration of the data collection process. This research reflects our ongoing efforts to enhance the usability and effectiveness of wearable technology, aspiring to contribute to future developments in the field.

The results of this paper indicate that when the actual forces exceed the range of the training data, the error significantly increases. Therefore, to enhance the prediction accuracy of the sensor in actual use, it is necessary to consider all possibilities within the range of the sensor during the training process. In conclusion, combining the data collection platform mentioned in our previous work and the data collection method described in this paper is a more rational and practical data collection scheme. The data collection plan based on the data collection platform can collect data near the full scale within the sensor's range without exceeding it, while the data collection scheme based on this study can provide more diverse and realistic data.

Looking ahead, we plan to collect data from more subjects in diverse and complex environments, not limited to walking at different speeds, and at various times. And we also plan to use data collection platform to gather a broader range of data within the sensor's capacity. By employing these methods and subtracting the initial value in the relaxed state to address sensor drift, the frequency of transfer learning will be reduced or potentially eliminated. Additionally, as observed in figure 7, there are indentations at the peaks of curves in Scenario 2. This is due to the subject actively lifting their leg during assistance, which increases the force tracking error. Future work will focus on enhancing the force tracking performance of the exoskeleton system through iterative optimization or other intelligent optimization algorithms.

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APPENDIX

Video:

https://www.bilibili.com/video/BV1uf421Q7Wu/?spm_id_from=333.999.0.0