Extracting Human-Exoskeleton Interaction Torque for Cable-Driven Upper-Limb Exoskeleton Equipped with Torque Sensors

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Abstract—Powered exoskeletons have global trends in broad applications, such as rehabilitation and human strength amplification in industry, military, and activities of daily livings. The motion intention of the exoskeleton wearer can be obtained using the interaction force at the physical human-machine interface. This work implements joint torque sensors in a custom-made cable-driven exoskeleton. The model of the torque sensor signal is established to extract the human-exoskeleton interaction (HEI) torque, which can be used to predict the human upper-limb motion intention. To accurately decouple the HEI torque from other components in the torque sensor signal, a nonlinear numerical friction model composed of the cable and joint parts is investigated based on the LuGre friction model. A protocol for parameter identification of the proposed friction model is verified experimentally. Furthermore, a coefficient combining the two friction models is designed for antagonistic directions in a joint to account for the bidirectional cable drive’s backlash and hysteresis characteristics. Owing to this coefficient, the error of the friction model is reduced by approximately 90% during motion direction change. Finally, the accuracy of the torque sensor model is verified experimentally, and the root mean square error (RMSE) is about 0.038 Nm (2.8%). The RMSE of extracted interaction torque is about 0.25 Nm (8.1%). This work validates the feasibility of extracting HEI torque via a torque sensor implemented in the upper-limb exoskeleton, which can promote the development of new generations of upper-limb exoskeleton for active rehabilitation or assistance and research on intuitive control of exoskeleton in future.

Index Terms—upper-limb exoskeleton; joint torque sensor; human-exoskeleton interface; cable-driven mechanism; friction modeling.

I. INTRODUCTION

Exoskeletons for human performance augmentation are complex wearable robotic systems with unique challenges, compared to other autonomous robotic systems [1]. In the past two decades, the use of powered exoskeletons for assistance and self-rehabilitation has attracted increasing attention in the fields of biomechanics and engineering [2]. This research area has focused on rehabilitation exoskeletons that utilize a ‘human in the loop’ system without the reliance on predefined rhythmic trajectories. Therefore, understanding the wearer’s motion intention in real-time is crucial for the exoskeleton to provide the required assistance.

Robotic exoskeleton interfaces can be classified into cognitive human-robot interfaces (such as brain-computer and electromyography-based interfaces) and physical human-robot interfaces (p-HRI) [3]. Compared to cognitive human-robot interfaces, p-HRI provide higher stability and accuracy, making them the principal candidate for understanding human movement intentions. In addition to the joystick, switch, and so on, the interaction force/torque, which is naturally existent in the human-exoskeleton coupling system, is widely used as the p-HRI in exoskeleton control.

Accurate acquisition of interaction forces directly impacts the control performance [4], which is critical for force control, assist-as-needed control [5], and compliance control. Relying on current sensors [6], sensor-less methods [7], or series elastic actuators (SEA) [8] for the detection of interaction forces fails to provide the required level of accuracy. Therefore, dedicated sensors such as 6-axis force/torque sensors, force sensing resistors (FSR) [9], or torque sensors are preferred, with each having its own merits and drawbacks when applied to human-exoskeleton coupling systems. The 6-axis force/torque sensors can directly measure interaction forces at a given point intuitively and accurately and have, therefore, been adopted by most of the existing exoskeletons and human-robot collaboration systems [10]. Usually, the subject must hold the grip attached to this sensor to apply human force, which limits the human-exoskeleton interaction mode and hinders the motor-sensory function of the human hand. This inherent defect makes it unsuitable for assistance in ADLs or upper-limb rehabilitation, where hand function is essential. Compared to torque sensors, FSRS are more affordable and convenient to use as they hardly influence the exoskeleton’s total weight and mechanical structure. However, they offer lower measurement repeatability and accuracy due to sensor drift and hysteresis [11].

Torque sensors have been widely used in industrial robots [12], collaborative robots [13] and lower limb exoskeletons [14], [15] as p-HRI. They enable the measurement of interaction...
forces at any contact point on the robotic arm and detect the sum of the multi-point interaction forces [16]. Without considering the passive compliance, a torque sensor can be regarded as an SEA with high stiffness, leading to an increased bandwidth in position or force control. Despite the introduction of torque sensors in some recent upper limb exoskeleton systems, those sensors have not been utilized as p-HRI. Zhang et al. [17] developed the Co-Exos system for upper limb rehabilitation which uses torque sensors to monitor motor output torques. Xie et al. [18] used the torque sensors in the FLEXO-Arm1 to record the motor driving torque during rehabilitation training, substituting the motor current signal. However, the potential of torque sensors for HEI torque detection has not been fully exploited. Therefore, this work utilizes the torque sensor as a p-HRI in a custom-made upper-limb exoskeleton. The developed system enables the user to move his/her arm naturally (within the exoskeleton) as the hand is freed from holding the handle of a 6-axis force/torque sensor. Additionally, the user can perform grasping or other hand movements and utilize the tactile sensation as feedback, enriching the application of the upper-limb exoskeleton in rehabilitation or assistance in ADLs. Moreover, the torque sensor has the potential of identifying the end-load, which has promising prospects in the development of the exoskeleton systems and control methods.

Despite their benefits, using torque sensors imposes a challenge for the process of extracting human-exoskeleton interaction (HEI) torque. This challenge arises from the fact that, unlike 6-axis force sensors, the torque sensor signals “include not only the active joint torque of subjects, but also undesired torque components, such as gravity torque, friction torque, inertial torque, and also passive joint torque of subjects” [19].

Among the torque components, friction is the most complex. Friction exists in mechanical systems as an inevitable disturbance. It is nonlinear and usually modeled in terms of Coulomb, viscous, stiction, and Stribeck friction [20]. It is worth mentioning that Stribeck friction is a nonlinear drop that occurs at low speeds during the transition from the maximum static friction to the Coulomb friction. An effective method for modelling nonlinear numerical friction is to characterize the four friction terms simultaneously (e.g. the Dahl [21] and LuGre [22] models). However, modeling cable transmission friction is more complex. Choi et al. [23] analyzed the cable tension and friction on cable-driven parallel robots based on the Dahl model. Miyasaka et al. [24] proposed a generic method for modeling friction on a cable-driven robot using the cable stretch model and the cable–pulley network friction model. Most exoskeleton systems, such as in [25], rely only on Coulomb and viscous friction terms for simplification. However, this simplification cannot be used with our exoskeleton, which adopts a unique cable transmission configuration comparable to open-ended pulley transmission and capstan transmission in [26]. The friction in such systems is particularly complex due to the presence of friction in the cable–pulley system, between the cable and the contact point, and at the exoskeleton joint. Therefore, a more accurate friction model should be established.

Having two antagonistic cables cooperate to drive the same exoskeleton joint can cause backlash. Backlash, in turn, can lead to deviation in joint angles and friction torque errors. While compensation methods, such as in [27], have been proposed to reduce the deviation in joint angle, the model of friction torque error is still unknown. In contrast to the traditional friction model, the friction existing in the bilateral cable transmission mechanism will not change abruptly when the speed crosses zero because of backlash. Thus, the friction models of both cables are integrated while taking backlash into account.

The main contributions of this paper are:

1. Implemented and modelled torque sensors in a cable-driven upper-limb exoskeleton. To our best knowledge, this is the first utilization of torque sensors as p-HRI in an upper-limb exoskeleton. This could promote the development of upper-limb exoskeletons by providing an alternative to using 6-axis force sensors.

2. Modelled the friction of the cable transmission mechanism. The friction on the cable and robotic joint were analyzed and a high-accuracy nonlinear numerical friction model was proposed. Subsequently, a protocol for parameter identification of this friction model was suggested, simplifying the process of modeling friction in complex setups.

3. Proposed and designed a friction combination coefficient. It is used to integrate the friction model of two cables into the friction term in the cable transmission mechanism and compensate the effect of backlash, which is put forward for the first time as far as we are aware.

The remainder of this article is organized as follows. Section II describes the main methods to extract HEI torque, including friction modeling, parameter identification, and friction modeling in antagonistic movements. The experimental results of the identification and verification of the proposed models are presented in Section III. Section IV discusses the utilization of the torque sensor and the establishment of the proposed model. Finally, Section V concludes this paper.

II. METHOD

A. Mechatronic System

The hardware of our exoskeleton prototype is shown in Fig. 1. The exoskeleton is fully portable and wearable with 3 degrees of freedom (DOFs), enabling shoulder abduction/adduction (Sh Ab/Ad), shoulder flexion/extension (Sh F/E), and elbow flexion/extension (El F/E). The backrest compactly houses the motor mechanism, driver module, embedded controller, battery and I/O board. Each drive module is equipped with a torque sensor (M2210A, Sunrise Instrument Company, China). The controller is based on the RT-Linux operating system and realizes the communication with motor servo drives through the EtherCAT bus. A Beckhoff terminal with extensibility is used for torque sensors signal sampling. The control frequency and sampling rate are both 1000 Hz, and the maximum delay is approximately 2us.

Fig. 2 depicts the configuration of the actuation part in the proposed exoskeleton, which is the experimental platform used in this paper. The phantom view in the middle of the three actuator modules shows the driving part of the elbow joint,
where the blue part is the winch capstan (cable driven pulley) to fix the cable, and the red part is the torque sensor. As illustrated in Fig. 1a and Fig. 2, a set of bidirectional cable-driven mechanisms starts from a winch capstan connected to the torque sensor and ends at an anchored point through the joint pulley. Two cables are fixed on the winch and function as a pair of antagonistic muscles to transmit forward and reverse power, respectively. Static analysis was used to determine the types of cables used. Both cables were made of stainless steel (#304). Cable 1 for the elbow joint flexion has a diameter of 1.2 mm and consists of 7 twisted strands formed by 7 individual wires. Cable 2 is composed of 7X1 twisted wires with a diameter of 0.8 mm. The cable is wound around some pulleys and friction exists at its contact point with the mechanical structure.

Fig. 1. Diagram of our exoskeleton hardware. (a) 3D model of the mechanical structure, (b) Electrical system.

where the elbow joint will be used as an example in this paper, including the various models, are illustrated in Fig. 3. The symbols and names of variables used are listed in Table I.

The elbow joint will be used as an example in the following models. The modular structure design enables the other joints to be modeled in the same way. When the exoskeleton is taken off, the dynamic model of single joint in an n-link robot can be expressed as:

\[
\mathbf{M}_R \ddot{\theta} + C_R \dot{\theta} + G_R = \tau
\]  

(1)

where the friction is ignored and the subscript R stands for robotic exoskeleton. The \(\mathbf{M}_R, C_R, \) and \(G_R\) can be calculated based on the Lagrangian dynamics method.

C. Torque Sensor Decoupling

For the human-exoskeleton coupling system, putting the total resistance and impetus on both sides establishes the dynamic equation as:

\[
\mathbf{M}_{H,R} \ddot{\theta} + \mathbf{C}_{H,R} \dot{\theta} + G_{H,R} + P_H + f = \tau_H + \tau_R
\]  

(2)

where \(P_H\) is the passive elastic torques of the human joint and the subscript \(H\) denotes human upper limb. For the human arm, the HEI torque notated as \(\tau_{HEI}\) is the extra power provided by the motor:

\[
\tau_{HEI} = \tau_R - (\mathbf{M}_R \ddot{\theta} + C_R \dot{\theta} + G_R + f)
\]  

(3)

Since forces result from mutual interactions, such that \(\tau_s = -\tau_s\), where the subscript \(s\) stands for torque sensor. Derived from (2) and (3), the torque sensor can be explicitly modeled as:

\[
(\mathbf{M}_R \ddot{\theta} + C_R \dot{\theta} + G_R + f) + \tau_{HEI} = -\tau_s
\]  

(4)

It can be seen from (4) that the torque sensor signal is composed of three components: dynamics, friction, and HEI torque. This formula is the focus of this paper, which means that the dynamics and friction terms should be precisely modeled to extract the HEI torque.

When the exoskeleton is taken off, the component of the

### Table I. Notation and Names of Variables

<table>
<thead>
<tr>
<th>Notation</th>
<th>Meaning</th>
</tr>
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<tbody>
<tr>
<td>(\mathbf{M})</td>
<td>the vector of mass terms in single joint space dynamics, and (\mathbf{M} \in \mathbb{R}^{1 \times 3})</td>
</tr>
<tr>
<td>(\mathbf{C})</td>
<td>the vector of Coriolis and centrifugal terms in single joint space dynamics, and (\mathbf{C} \in \mathbb{R}^{1 \times 3})</td>
</tr>
<tr>
<td>(G)</td>
<td>the gravity terms in single joint space dynamics, and (G \in \mathbb{R}^{1 \times 3})</td>
</tr>
<tr>
<td>(\theta)</td>
<td>position in joint space, and (\theta \in \mathbb{R}^{1 \times 3}), whose derivative (\dot{\theta}) and (\ddot{\theta}) represent joint velocity and acceleration respectively, (\ddot{\theta} \in \mathbb{R}^{1 \times 3}) refers specifically to the value at the elbow joint in the friction identification part.</td>
</tr>
<tr>
<td>(x)</td>
<td>displacement of the cables, and (x \in \mathbb{R}^{1 \times 1}) refers specifically to the value at the transmission of elbow joint in the friction identification part.</td>
</tr>
<tr>
<td>(\tau)</td>
<td>torques of a single joint, and (\tau \in \mathbb{R}^{1 \times 2})</td>
</tr>
<tr>
<td>(f)</td>
<td>the friction terms in single joint space, and (f \in \mathbb{R}^{1 \times 1}) refers specifically to the value at the elbow joint.</td>
</tr>
<tr>
<td>(T)</td>
<td>the cable tension, and (T \in \mathbb{R}^{1 \times 1})</td>
</tr>
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torque sensor signal can be reduced to

$$
\mathbf{M}_R \ddot{\mathbf{q}} + \mathbf{C}_R \dot{\mathbf{q}} + \mathbf{G}_R + \mathbf{f} = -\mathbf{\tau}_s
$$

(5)

This circumstance excludes the interference of the active force of the human body, so that the friction force can be modeled more conveniently and precisely.

D. Friction modeling

Friction is an inevitable non-linear term in robot modeling. According to the position of the torque sensor, the frictional force of the cables $f_c(\dot{x})$ and the frictional torque of the robotic joint $f_j(\dot{\theta})$ will be incorporated into the torque sensor signal. The friction term in elbow joint can be modeled as:

$$
f = f_c(\dot{x}) + f_j(\dot{\theta})
$$

(6)

The LuGre [22] friction model is adopted and simplified as:

$$
f_{\text{LuGre}} = a + b e^{-c \dot{x}} + d \dot{q}
$$

(7)

where $a$, $b$, $c$, and $d$ are the parameters that need to be identified. The variable $q$ represents position, which is replaced by $x$ and $\theta$ in this paper to represent the position of cable and joint, respectively. The three terms in (7) correspond to Coulomb friction, the Stribeck friction, and viscous friction respectively. Therefore, the joint friction torque can be modeled as:

$$
f_j(\dot{\theta}) = a_j + b_j \cdot e^{-c_j \dot{\theta}} + d_j \cdot \dot{\theta}
$$

(8)

and the subscript $j$ denotes the joint. The friction between the cable and the different parts in contact with it can be summed to get the cable friction. The cable has 5 contacts with other parts in our exoskeleton, two of which are pulleys, and the rest are point contacts. Point contacts can be considered as pulley contacts with a minimum diameter to allow the cable friction to be modeled as a cascade cable pulley system, which is:

$$
f_c(\dot{x}) = \sum_{i=1}^{5} \mu_i \cdot F_{NI} + b_i \cdot e^{-c_i \dot{x}} + d_i \cdot \dot{x}
$$

(9)

where the subscript $i$ is the number of the pulley, the subscript $c$ denotes the cable, $\mu_i$ is the friction coefficient, and $F_{NI}$ is the normal force. During Coulomb friction modeling, the normal force can be obtained from the cable tension applied to the pulley by the law of cosines [23]:

$$
F_{NI} = \frac{T_i^2 \cos \alpha_i + \alpha_i^2}{1 + 2T_i^2 \cos \alpha_i + \alpha_i^2} T_i
$$

(10)

where $T_i$ is the cable tension after passing the $i$-th pulley, and $T_0$ is the cable tension on the winch capstan, satisfying $T_i = T_{i-1} - f_{ci}$. $\alpha_i$ is the wrapping angle of $i$-th Pulley. Define $\lambda_i = T_i / T_{i-1}$ as the loss factor of the $i$-th pulley and (10) can be simplified as:

$$
F_{NI} = \frac{1 - 2\lambda_i \cos \alpha_i + \lambda_i^2}{1 + 2\lambda_i \cos \alpha_i + \lambda_i^2} T_i
$$

(11)

Define $\gamma_i = \frac{1 - 2\lambda_i \cos \alpha_i + \lambda_i^2}{1 + 2\lambda_i \cos \alpha_i + \lambda_i^2}$, then

$$
F_{NI} = \gamma_i T_{i-1} = \gamma_i (\prod_{k=1}^{5-k} A_k) T_0
$$

(12)

Therefore, Equation (9) can be rewritten as:

$$
f_c(\dot{x}) = \sum_{i=1}^{5} \left[ \mu_i \gamma_i (\prod_{k=1}^{5-k} A_k) T_0 + b_i e^{-c_i \dot{x}} + d_i \dot{x} \right]
$$

$$
= \left[ \sum_{i=1}^{5} (\mu_i \gamma_i (\prod_{k=1}^{5-k} A_k) T_0) + \sum_{i=1}^{5} (b_i e^{-c_i \dot{x}}) + \sum_{i=1}^{5} (d_i \dot{x}) \right]
$$

(13)

where $\gamma_c$ is the equivalent coefficient of friction of the cable.

The complete friction model (6) can be rewritten as:

$$
f = r_1 f_c(\dot{x}) + r_2 f_j(\dot{\theta})
$$

$$
= r_1 \left[ \eta_c T_0 + b_1 e^{-c_1 \dot{x}} + d_1 \dot{x} \right]
$$

$$
+ \left[ a_j + b_1 \cdot e^{-c_1 \dot{\theta}} + d_j \cdot \dot{\theta} \right]/r_2
$$

(14)

$$
f = r_1 \left( \eta_c T_0 + \bar{a}_j + b_1 e^{-c_1 \dot{x}_2} + d_1 \dot{x}_2 \right)
$$

$$
+ \left[ a_j + b_1 \cdot e^{-c_1 \dot{\theta}} + d_j \cdot \dot{\theta} \right]/r_2
$$

(15)

where $r_1$ and $r_2$ are the diameter of the winch capstan and joint pulley respectively; $\theta = \theta_1$ and $x = \theta - r_2$; the line mark above the symbol indicates the equivalent value after synthesis. Finally, two groups of 7 parameters ($P = [\eta_c, \bar{a}_j, b_1, c_1, \bar{b}_j, c_2, \bar{d}_j]$) needed to be identified for two different cables.

E. Friction Identification

In the previous section, an accurate theoretical friction model was obtained, where the coefficients need to be identified experimentally.

To simplify the calculation, uniform motions in joint space were adopted as the excitation trajectory in the experiment, and the angle of other two joint was fixed as a constant. Under this circumstance, $\dot{\theta} = 0^{\circ}$, $\dot{\theta}_1$, $\dot{\theta}_2 = 0$, and $\mathbf{C}_R = 0$, where the number in the subscript represents the i-th value in the vector; $\mathbf{G} = \mathbf{M}_3 \mathbf{g} r_3 x \sin \theta$, where $r_3 x$ is the distance of centroid in the $x$ direction; and $-\tau_s = r_1 T_0$. Finally, $\tau_s = 1 - \eta_c$. $\mathbf{M}_3 \mathbf{g} r_3 x \sin \theta$.

$$
-\tau_s = 1 - \eta_c
$$

$$
= \frac{1}{1 - \eta_c} \left[ r_1 \left( \bar{a}_j + b_1 e^{-c_1 \dot{x}_2} + d_1 \dot{x}_2 \right) + \bar{d}_j \cdot \dot{\theta} \right]
$$

(16)

Finally,

$$
-\tau_s = \frac{1}{1 - \eta_c} \left[ r_1 \left( \bar{a}_j + b_1 e^{-c_1 \dot{x}_2} + d_1 \dot{x}_2 \right) + \bar{d}_j \cdot \dot{\theta} \right]
$$

(17)

$$
= A \sin \theta + B
$$

(18)

$$
B = \frac{r_1}{1 - \eta_c} \left( \bar{a}_j + b_1 e^{-c_1 \dot{x}_2} + d_1 \dot{x}_2 + \bar{d}_j \cdot \dot{\theta} \right)
$$

(19)

where $A$ and $B$ are the two parameters that need to be identified. Taking $\sin \theta$ as the independent variable and $\tau_s$ as the dependent variable, this problem is essentially a linear fitting problem. Obviously, by changing the speed of the excitation trajectory, a set of values of $A(\dot{\theta})$ and $B(\dot{\theta})$ can be obtained. It
can be seen from (18) and (19) that A is a constant value independent of joint speed in contrast to B, so that the $\eta_{ce}$ can be obtained by (18) and then substituted into the (19). The other 6 parameters can be identified through curve fitting using (19). The Levenberg-Marquardt (LM) algorithm is used to extract these parameters and can be replaced with other optimization algorithms as needed.

Using this method, the friction model parameter identification steps are:

1. Experiment: Employ the uniform motions in joint space with different speeds as the excitation trajectories.
2. Acquire $A(\dot{\theta})$ using (17). For each trial, take the sine transform of the joint position and perform linear fitting with the torque data, thereby obtaining the parameter $A(\dot{\theta})$.
3. Determine the value of $A$. Since $A$ is a constant, the mean value of $A(\dot{\theta})$ is taken as the result.
4. Acquire $B(\dot{\theta})$ using (17). For each trial, substitute $A$ to (17), calculate the residual error between A and the sensor data, and the mean value of the residual error is $B(\dot{\theta})$.
5. Determine parameters $P$ of the friction model. Determine $\tilde{\eta}_c$ using (18). Perform curve fitting on $B(\dot{\theta})$ according to (19) and multiply the coefficient to get the result.

Two cables were modeled by two sets of $P$ separately using data from two speed directions, forming the two friction model $f_{up}(\dot{\theta})$ and $f_{down}(\dot{\theta})$. Usually, the final friction model combines the two models by coefficient $K_f$:

\[ \tilde{f}(\dot{\theta}) = \left\{ \begin{array}{ll} \tilde{K}_f f_{up}(\dot{\theta}), & \tilde{K}_f = 1, \dot{\theta} \geq 0 \\ \tilde{K}_f f_{down}(\dot{\theta}), & \tilde{K}_f = -1, \dot{\theta} < 0 \end{array} \right. \]  

$\tilde{K}_f$ is a coefficient related to the direction of velocity, which is the same as $K_f = \text{sign}(\dot{\theta})$.

**F. Friction Combination model**

Equation (20) leads to a phenomenon where the friction force will result in a spike when the motion direction is suddenly reversed. The speed $\dot{\theta}$ was obtained by differentiating the position, which can also cause the above situation when the sampled joint position single is jerky.

For this, a simple adaptive coefficient $K_f(k)$ is designed, where $k$ is the discrete time point. Considering the conditions:

1) When the cable acted as the joint flexor is tensioned and pulled to the bend the joint, the friction is exactly equal to $f_{up}(\dot{\theta})$, and the $K_f(k)$ should be 1.

2) In the reverse movement, the frictional force is equal to $-f_{down}(\dot{\theta})$, and $K_f(k)$ should be -1.

3) When the motion direction has just changed, the friction force continuously transits from one of $f_{up}(\dot{\theta})$ and $-f_{down}(\dot{\theta})$ to the other. After the winch capstan rotates for a very short time, the cable would be tensioned and the displacement generated on the cable (backlash) is defined as the clearance $X_f$. During this short period of time, the direction of friction reverses while $K_f(k)$ gradually transitions between 1 and -1.

Ignoring the accurate relationship between the position $x$ and coefficient $K_f$, and considering the correspondence between their extreme values, a linear mapping can be established as:

\[ \frac{x(k) - x(n)}{X_{ct}} = \frac{K_f(k) - K_f(n)}{1 - (-1)} \]  

where $n$ is the time point when direction changed, and $n \leq k$. Difference the (21), so that

\[ \frac{x(k) - x(k-1)}{X_{ct}} = \frac{K_f(k) - K_f(k-1)}{2} \]  

\[ \Delta K_f(k) = K_f(k) - K_f(k-1) = 2 \cdot r_1 \cdot \dot{\theta}(k)/X_{ct} \]

Thus, the recursive calculation formula of $K_f$ is obtained:

\[ K_f(k) = K_f(k-1) + \Delta K_f(k), K_f(k) \in [-1,1] \]

Since the equation is established only considering the neighborhoods of the time $n$, the initial value $K_f(0)$ is not strictly defined and can be corrected after a period of time. Ultimately, the complete friction model is:

\[ f(\dot{\theta}_k) = f_{down}(\dot{\theta}_k) + \frac{1}{2} \left( f_{up}(\dot{\theta}_k) - f_{down}(\dot{\theta}_k) \right) \]

This model is the established friction combination model of the bidirectional cable transmission mechanism, which is derived from the hypothesis that the relationship between $K_f$ and displacement $x$ is linear. It will be referred to as the linear friction combination model.

Although such an interpretable model generally solves the problem of combining the two friction models of the antagonistic cables, it is inaccurate. In fact, it can be assumed that there is a marginal effect here. When the rope is just slack, the change in cable tension will be huge. Therefore, there may be a nonlinear relationship between friction and displacement, and (21) should be expressed as:

\[ \tilde{F} \left[ \frac{x(k) - x(n)}{X_{ct}} \right] = \frac{\tilde{K}_f(k) - \tilde{K}_f(n)}{1 - (-1)} \]

where the wave symbol represents nonlinearity and $\tilde{F}[\ ]$ is a nonlinear function that needs to be designed. Following the same derivation, the corresponding equations are:

\[ f(\dot{\theta}_k) = f_{down}(\dot{\theta}_k) + \tilde{K}_f(k) \left( f_{up}(\dot{\theta}_k) - f_{down}(\dot{\theta}_k) \right) \]

\[ \tilde{K}_f(k) = \tilde{F}[K_f(k)], \tilde{K}_f(k) \in [0,1] \]

The above model will be referred to as the nonlinear friction combination model.

Considering the range and monotonicity of this target function, it is designed as:

\[ \tilde{K}_f = k \cdot \text{arctan}[p \cdot (K_f + 1)] \]

where $k$ and $p$ are parameters that need to be identified. The power function was selected as a comparation, whose model with parameter $n$ is:

\[ \tilde{K}_f' = \left( (K_f + 1)/2 \right)^n \]

In the same way, the LM algorithm is used to identify the above parameters. So far, the nonlinear friction combination
model in torque sensor signal is established by (23), (27) and (29), and the torque sensor is completely modelled by (4), (15) and (27).

III. EXPERIMENT AND RESULT

A. Parameter Identification of Friction model

In this experiment, 20 joint speeds were selected to generate the excitation trajectory, and each speed was repeated in 3 trials. The trajectories were uniform linear movements from 0° to 90° and then from 90° to 0°. The signal noise was reduced by preprocessing the torque sensor signal using a 4th-order Butterworth low-pass filter with a 5 Hz cutoff frequency and zero phase delay. The data were processed offline and the filter has zero phase delay.

The friction identification experiment consisted of five steps as proposed in Section III.E. In step 2, the linear fitting of trials on cable 1 and cable 2 resulted in an averaged R-square of 0.8961 and 0.7648, and RMSE of 0.0238 Nm and 0.0202 Nm, respectively. In step 3, the parameter identification results of \( A \) were 0.3510 Nm and 0.3388 Nm respectively. The standard deviation or RMSE was 0.0126 Nm and 0.0119 Nm respectively, and the relative error was 3.5% and 3%. Thus, the results of \( A \) were considered reliable and, therefore, used in the subsequent step. The results of the above indices were partially influenced by the noise of the torque sensor. In step 5, the parameter vector \( P \) of the friction model was identified by the LM algorithm, as is presented in Table II. The R-square was 0.99 and 0.86 while the RMSE was 0.0033 (0.4%) and 0.0024 (0.7%), respectively.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>( \eta_c )</th>
<th>( a_t )</th>
<th>( b_t )</th>
<th>( c_t )</th>
<th>( b_j )</th>
<th>( c_j )</th>
<th>( a )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value of cable 1</td>
<td>0.4089</td>
<td>1.5019</td>
<td>0.1943</td>
<td>199.2</td>
<td>0.1077</td>
<td>76.67</td>
<td>0.04176</td>
</tr>
<tr>
<td>Value of cable 2</td>
<td>0.3877</td>
<td>-0.3111</td>
<td>-0.1032</td>
<td>-38.73</td>
<td>-0.1852</td>
<td>-1.332</td>
<td>0.02684</td>
</tr>
</tbody>
</table>

Fig. 4 depicts the sample points and fitting curve of \( \mathbf{B}(\hat{\theta}) \), which reflects the friction characteristics of the exoskeleton elbow joint except for \( \eta_c \). This figure illustrates the equivalent friction torque detected by the torque sensor, which is related to the diameter of the pulley \( r_1 \) and the equivalent friction coefficient \( \eta_c \). The actual friction model is described by the parameters from Table II, such as the Coulomb friction torque in joint was 1.50 Nm and 0.31 Nm respectively. When using this friction model and parameters to fit the original (unfiltered) torque sensor signal, the RMSE is 0.0276 Nm and 0.0274 Nm, respectively.

B. Evaluation of the torque sensor signal model

1) Evaluation of the torque sensor model with linear friction combination model

The precise establishment of the torque sensor model is the focus of this article. Thus, we calculated the dynamic parameters using the Solidworks software and identified the friction parameters through experiments. Following the previous sections, the torque sensor model has been entirely defined by (5), with the friction term modeled by (15) and the linear friction combination model by (25).

Sine or cosine signals are often selected as the excitation trajectories for evaluation. The experiment was carried out at the elbow joint while the other two joints were fixed at 0°. The cascaded cosine signals of different frequencies were selected as the excitation trajectory, and the fundamental period of cosine signal was 160 seconds. Multiples (1, 2, 10, 20, and 100 times) of the fundamental frequency were chosen as the frequency of the cascaded cosine signal, ranging from 0.00625 Hz to 0.625 Hz. Finally, each trial lasted 265.6 seconds and was repeated 3 times. The trajectory ranged between 20 and 60 degrees of the elbow angle.

The results of the verification experiments are shown in Fig. 5. The estimated values in the figure were predicted by the torque sensor model using the linear friction combination model with \( K_f \) in (25). The torque sensor signal calculated by the model is in agreement with the actual results of the three trials, which were composed of friction, gravity, inertia, Coriolis force and centripetal force. In this experiment, the Coriolis force and the centripetal force were zero, and the other three components were plotted. The magnitude of the inertial forces was small due to the mass’s value and the centroid’s location and was only reflected under high acceleration. Undeniably, friction was considerable compared to the gravity in the exoskeleton. The error curves in the bottom plot reflect the accuracy of the model. After moving in the same direction for a period of time, the backlash is eliminated and the cable is tensioned, resulting in error values close to 0 Nm with a mean absolute error (MAE) of 0.0220±0.0001 Nm (1.69%) and a RMSE of 0.0298±0.0006 Nm (about 2.29%). When the motion
direction just changed, the peak error reached 0.4 Nm and -0.4 Nm. The results of this step verified the accuracy of the torque sensor model in the period without the influence of backlash. The performance during direction changes could be improved by identifying the nonlinear friction combination model.

2) Parameter Identification of nonlinear friction combination model

The design process and results of the nonlinear function $\hat{f}[x]$ are shown in Fig. 6. The data used was limited to when $K_f$ is not equal to 1 or -1 as motion direction change is the main area of interest. It can be seen from Fig. 6a and 6b that there is an overlap in the multi-times data of motion direction change, and that there is indeed a nonlinear relationship between the two groups, indicating the existence of an inherent law. Fig. 6c and Fig. 6d were obtained by dividing the changed friction value by the maximal change of friction value. The y-axis represents the process of motion direction changing, and the Fig. 6d is rotated as the $K_f \_{\text{new}}$ changed from 1 to -1. The real progress of motion direction changing was expected to be modeled by $K_f \_{\text{new}}$, so that a nonlinear function in (28) would be fitted to the two sets of data in Fig. 6c and 6d. The results are shown in Fig. 6e and Table III. It could be seen from the Fig. 6e that the arctangent function model is a good fit to both forward and backward data. The R-square was 0.994 and the RMSE was 0.0260±0.0177 (2.6%). The accuracy and generality of the model were verified by these two indices.

![Fig. 6. Design of the nonlinear friction combination model $K_f$. Sub-plot (a) and (b) show the predicted friction value from the linear friction combination model (in red) and the measured value (average of 3 trials, in blue), taking $K_f$ as the x-axis. Sub-plot (c) and (d) are the normalization results of the left 2 subfigures. Sub-plot (e) shows the fitting results.](image)

### TABLE III

<table>
<thead>
<tr>
<th>Parameters</th>
<th>$k$</th>
<th>$\rho$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>0.752</td>
<td>2.011</td>
</tr>
</tbody>
</table>

3) Evaluation of the torque sensor model with nonlinear friction combination model

Based on the above results, the experimental data were re-evaluated using the torque sensor model with nonlinear friction combination model, and the results are shown in Fig. 7. Compared with Fig. 5, the model used in Fig. 7 only changed the friction combination model with a nonlinear model. Therefore, the difference only existed in the period when the moment direction changed. The results at other times were deservedly the same as that in section III.B.1, and not retold here. Using this method, the maximum error of the torque sensor model was reduced from 0.4 Nm to 0.13 Nm. In other words, the accuracy was improved by 67.5% when the moment direction changed. Over the whole time series, the MAE is 0.0349±0.0033 Nm and the RMSE is 0.0429±0.0045 Nm, meaning that the relative error of the model is about 3%.

In addition, the coefficient $K_f$ designed in this paper improved the estimation accuracy of the friction during direction change. Fig. 8 depicted three scenarios to emphasize the effectiveness of this method. Introducing this coefficient reduced the peak error, which was greater than 1 Nm without it, by about 90%. If the human-machine interaction (HMI) torque term is introduced, the so-called error here is the HMI torque extracted from the torque sensor signal. Therefore, this coefficient will effectively improve the accuracy of the extraction of HEI torque from a cable-driven exoskeleton.

![Fig. 7. Results of evaluation of torque sensor model (using nonlinear friction combination model) under sinusoidal excitation trajectory. It has the same excitation trajectory and similar picture composition as Fig. 5.](image)

![Fig. 8. Comparison of the error of torque sensor model with and without the coefficient $K_f$ and $\hat{K}_f$. (a) Partial enlargement of time series. (b) Statistical results of absolute value of error. Data were expressed as mean ± SD. Stable state means that the cable is tensioned, while the transition state means that the cable is slack caused by backlash when the direction of motion changes. Furthermore, the proposed model and identified parameters were evaluated using a complex experimental paradigm.](image)
Because of the motion-coupling defect existing between the cable-driven joints Sh F/E and El F/E, which will be optimized in the future structural design, the Sh F/E was controlled to remain stationary. The El F/E joint was driven with Sh Ab/Ad movements simultaneously. The range of motion was also expanded from 40° to 90° (restricted by the structural design) but the parameters in the model of f and \( \bar{f} \) remained unchanged. This experiment was repeated 3 times, and the designed trajectory and results could be found in the Fig. 9. The error plots in Fig. 9 are close to 0 Nm with a MAE of 0.0307±0.0044 Nm (2.24%) and a RMSE of 0.0386±0.0046 Nm (2.82%). When the motion direction just changes, the peak error reaches 0.16 Nm under normal speeds and 0.33 Nm under relatively high speeds.

The focus of this experiment was the effective interactive torque on the elbow joint, and, therefore, a load cell was installed at the end of the robotic forearm to measure the tensile or compressive forces perpendicular to the forearm. It was manifest from the Fig. 10a that the load cell was fitted with a bolt as a handle, and was fixed to the exoskeleton forearm by a clamp. The interaction force, and then multiplied by the moment arm to calculate the interaction torque. This value was regarded as the single-point contact force, and the corresponding equation is:

\[
(M_e \ddot{\theta} + C_R \dot{\theta} + G_R + f) + \tau_E = -\tau_s
\]

where \( \tau_E \) is an external single-point contact force instead of \( \tau_{HEI} \) in this experiment.

Before the experiment, the load cell was horizontally fixed on the table and calibrated by weights. As its output is affected by gravity, the signal baseline changes during the experiment. A pre-test without interaction force was carried out, to collect the baseline output of the load cell under cosine trajectory. During the actual experiment, the difference between the values obtained and the baseline was regarded as the extraction interaction force, and then multiplied by the moment arm to calculate the interaction torque. This value was regarded as the true value to evaluate the calculated interaction torque.

Fig. 10b and Fig. 10c demonstrated the results of the interaction experiments. A low-pass filter with a 5 Hz cut-off frequency was used to smooth the raw signals. It could be seen that the human-exerted interaction forces possessed different directions, amplitudes and durations, resulting in experimental results that better reflect reality. In Fig. 10b, the MAE was...
0.1407 Nm (9.6%) and the RMSE was 0.2429 Nm (17.3%). The results of these indices were affected by the time response characteristic of different sensors and the backlash in the cable-tendon actuation system. Looking at the peak torque value during each interaction, the error was 0.0234 Nm (about 1.6%). In Fig. 10c, during the period of interaction, the MAE was 0.1731 Nm (5.6%) and the RMSE was 0.2513 Nm (8.1%).

IV. DISCUSSION

A. Physical HMI

Mounting multi-axis force sensors on the end effector has been widely used in upper limb rehabilitation exoskeleton, such as [12], [28]–[30], as a simple way to achieve p-HMI. It is necessary to ensure good contact when using a multi-axis force sensor. Thus, a grip is often used to connect with the human hand, limiting its motor-sensory function. Recently, Yves et al. [31] placed the sensors between the exoskeleton arms and the cuffs to avoid the grip but the wrist joint movement was still restricted. Sun et al. [32] also developed exoskeletons with similar structures, and mentioned the problem of signal redundancy, which the use a set of 6-axis F/T sensors would exacerbate. Nevertheless, the interaction between a human and exoskeleton is complex and extends beyond the end effector or a few contact points [18]. Therefore, from the perspective of hand function, the torque sensor is a more suitable interface for physical HMI between the limb and exoskeleton and has the ability to detect interactions with the environment or the objects held by the hand.

However, torque sensors also have their shortcomings. They detect torque signals in only one dimension, so each robotic joint must be equipped with a separate torque sensor. As more DOFs are added (e.g., 6 or 7), the mechanism will eventually become more complicated and bulkier than the multi-axis force sensor. In addition, due to space limitations, the torque sensor is more difficult to install directly in forearm rotation or wrist joint movement. In summary, torque sensors are more suitable for exoskeletons with limited DOFs covering gross motor functions. As a complement, the motor-current-based senseless method on HEI torque estimation is feasible for fine movement, which can also adopt the method proposed in this paper. To simplify the robotic arm structure and reduce burden on the human arm, this design places the torque sensor at the actuator module mounted in the backrest. The performance of the torque sensor in HEI torque extraction will improve if installed directly at the joint.

B. Modeling of torque sensor and friction

Because of the modular joint design, this paper takes the elbow joint as an example. In addition to the proposed method being applicable to other joints, it is also applicable to model motor current signals.

A benefit of cable transmission is that the mass of the link of the robotic arm is light, so the inertial force, centripetal force and Coriolis force are very small, which could be seen in Fig. 10. Unlike the Bowden cable transmission, whose friction has a universal situation and a well-studied characterization [33], the friction of the cable in our exoskeleton is more complex and influenced by the specific mechanical structure. Therefore, a sophisticated friction model, the LuGre model, was adopted and the friction model of the rope-pulley system was analyzed to characterize it. The LuGre friction model has been proved to be the most suitable model for actuators made of piezoelectric materials [34], which is similar to the system in this paper in terms of the nonlinear and hysteresis characteristics. After simplification, the final friction model retains two exponential function terms. A further simplified model with one combined exponential function term was also tested and acquired a similar accuracy, but the interpretability is worse. In contrast, many researchers use a neural networks to model or compensate the friction [12], and regard it as a black-box system. In [35], Just et al. established the friction compensation model of the ARMin exoskeleton with an exponential function. The exponential function in their study was related to cable tension, as derived in [8], which is different from this paper. However, the disadvantage of cable transmission is mainly related to the extra friction and vibration.

The coefficient $\hat{K}_f$ reduces the prediction error of the model significantly. In essence, this coefficient reflects whether the cables are tensioned, whose value of 1 or -1 indicates that cable 1 or cable 2 has been fully tensioned, respectively. It utilized the hysteresis characteristic and the backlash in the cable transmission mechanism to ensure that the friction is continuously changing, avoiding the jitter of the model-predict friction value when the speed is zero-crossing or jittering caused by derivation. The relationship between the linear combination model and reality was modeled by an arctangent function. It was designed with the consideration that the function should be convex and have an appropriate definition field and a value field. The power function had similar characteristics and was selected as a comparison to highlight the validity of the arctangent function.

The literature is sparse in relation to the friction combination method established in this paper using $\hat{K}_f$. It has been shown that having enough pre-tension on the bi-directional transmission cable can achieve 0 backlashes [30]. However, pre-tightening the cable to eliminate backlash can be difficult, and the method introduced in this paper solves this problem. Although a pre-tension mechanism was designed, a backlash of approximately 0.8 mm was still present. The $\hat{K}_f$ was therefore proposed to account for this backlash and showed excellent potential for avoiding the jitter in the model-predict friction value.

C. Experimental results

During the parameters identification of the friction model, the coefficient of variation (CV) of each parameter can be calculated based on the confidence bounds. For cable 1, $\tilde{a}_j$ had the lowest CV (2.9%) and $\tilde{d}_j$ had the highest (57.4%). The corresponding values for cable 2 were 1.4% and 30.0%, respectively. Since the bottom control layer of the exoskeleton has a maximum speed limit as a safety precaution, no experimental data was collected under high-speed motion.
When the joint is moving at high speed, the flexibility of the cable and the existence of backlash increase the vibration of the torque signal. Therefore, the coefficient of viscous friction $\dot{\theta}$ characterizing friction in high-speed motion may be inaccurate, which is also discussed in [36].

A load cell was used to measure the actual value of the interaction force. When the elbow angle is fixed, Fig. 10b shows that the detected peak value of the torque sensor is almost the same as that of load cell. However, the backlash in cable transmission causes a delay in the torque sensor’s detection of the interaction onset, thus making the error bigger. This condition is relieved during joint movement in Fig. 10c but the peak value detection becomes worse. Although we have modeled and compensated the friction force, the interaction force transmitted to the sensor through the cable will inevitably be affected by the friction of the cable in motion. This contributes to the error in the interaction peak in Fig. 10c.

The installation of the load cell changed the mass of the robotic forearm. The cables were re-tightened accordingly for improved performance which also resulted in a change in backlash. These parameters were updated in Fig. 10c, but the nonlinear friction combination model parameters remained unchanged (Table 3), proving the universality of the nonlinear friction combination model.

It can be concluded that experimental results have shown the proposed method to be acceptable in accuracy and robustness. This improved performance is mainly due to the consideration of the Stribeck friction. We speculate that the Stribeck effect in friction is related to the bearing used in the cable pully and robotic joint.

D. Limitations and future works

This article focused on the terms related to the exoskeleton, ignoring the dynamic parameters related to humans. Modeling and parameters identification on $P_h$ have been studied in lower-limb exoskeletons, but further research is required for upper-limb exoskeletons. Therefore, the purpose of this article is to verify the feasibility of using torque sensors to accurately extract HEI torque from a novel cable-driven upper-limb exoskeleton. At this stage, no user experiments have been carried out. Although using exponential functions to fit the velocity-friction curve achieved good results, its nonlinearity could lead to difficulties in online parameter identification. This paper designed a nonlinear friction combination model in the form of an arctangent function. No similar references have been found yet, and its excellent performance is difficult to explain. This problem can be thoroughly explored by setting up a cable transmission test bench, rather than using an exoskeleton structure.

In future work, we will strive to model the human arm dynamics specifically. Following that, the human active torque can be extracted from the HEI force. Compliance control and assist-as-needed control can be achieved using the human active torque extracted from the torque sensor.

V. CONCLUSION

This paper established the model of the torque sensor signal in a novel cable-driven upper-limb exoskeleton. The friction was modeled using a nonlinear numerical function based on the LuGre model. A friction combination coefficient was designed to prevent the jerk in friction when the motion direction is reversed and alleviate the hysteretic characteristics of bidirectional cable drive (backlash). This coefficient connects the two friction models of the positive and negative directions of a joint. The accuracy of the torque sensor model was verified by experiments allowing the interaction force to be precisely extracted. Achieving such results depended on the accurate modeling of friction and the design of the friction combination coefficient. To the best of our knowledge, this is the first demonstration of using torque sensors as a physical HMI in an upper limb exoskeleton. In doing so, the usage of a multi-dimensional force sensor in the end effector is avoided and hand functionality remain available to the user. This work laid a foundation for a new generation of exoskeletons towards active rehabilitation or effective assistance of upper limbs in ADLs.

REFERENCES


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