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Self-learning Assistive Exoskeleton with Sliding Mode Admittance Control

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Abstract— **Human intention estimation is important for assistive lower limb exoskeleton, and the task is realized mostly by the dynamics model or the EMG model. Although the dynamics model offers better estimation, it fails when unmodeled disturbances come into the system, such as the ground reaction force. In contrast, the EMG model is non-stationary, and therefore the offline calibrated EMG model is not satisfactory for long-time operation. In this paper, we propose the self-learning scheme with the sliding mode admittance control to overcome the deficiency. In the swing phase, the dynamics model is used to estimate the intention while teaching the EMG model; in the consecutive swing phase, the taught EMG model is used alternatively. In consequence, the self-learning control scheme provides better estimations during the whole operation. In addition, the admittance interface and the sliding mode controller ensure robust performance. The control scheme is justified by the knee orthosis with the backdrivable spring torsion actuator, and the experimental results are prominent.**

I. Introduction

In design of the assistive exoskeleton, the estimation of the human intention is critical. By human intention, we mean the desired movement of the operator. According to different implementations, we categorize the literatures into two approaches. The first approach measures the interaction force between the exoskeleton and the operator with force sensors [1, 2]. However, this approach reduces the payloads only when the operator interacts with the surrounding. Exercising alone, the operator consumes at least the same work as that without the exoskeleton. The second approach is the model-based approach: the dynamics model [3, 4] and the Electromyography (EMG)-model [5, 6]. The dynamics model uses inverse dynamics to compute the human intended torque. However, the estimation error is large in the presence of the unmodeled disturbances. On the contrary, the EMG-model measures directly the level of the human intended torque by the activated EMG signal, but it suffers from the time-variant nature. Summarizing the literatures, most of the model-based exoskeleton systems can be regarded as the human torque amplifier, so the operator feels assisted even without the interaction with the environment.

The EXO-UL7 [1] used three force sensors to estimate the interaction between human and robot, and the position trajectories of upper limber exoskeleton were generated by the admittance model. In [2], the similar admittance model was adopted with the force sensors on the fingers. Moreover, they included the sliding mode control to overcome the mechanical parameters uncertainties due to deflection of Bowden cables and the disturbance. In both designs, the objective is to minimize the interaction force between the user and the robot so that the robot follows the motion of the user. This design, however, does not directly minimize the loading of the operator. In fact, the control scheme only lowers the impedance between the exoskeleton and the user. In assistive applications, the exoskeleton should provide additional power to support the user.

Considering the unmodeled disturbance in the dynamics model, the adaptive control in Knee Orthosis [7] tracked the predefined trajectory and adjusted the dynamics parameters online. In [8], they identified the parameters of the model for the lower limb offline, and controlled the knee orthosis by the high-order sliding model controller to overcome the uncertainty of the online parameter estimation. Because the robots in [7, 8] were used in rehabilitation, the position trajectories were predefined by the doctor or the user. No online feedback of the operator's intention is presented, yet it is crucial to estimate the human intention and to control the robot accordingly for assistive exoskeletons.

Combing the benefits of both the dynamics model and the EMG model, we propose the self-learning scheme for human walking assistance with the sliding mode admittance control. During the swing phase, the inverse dynamics model estimates the human intended torque and teaches the EMG model with the estimation. The taught EMG model is then used in the consecutive stance phase to overcome the disturbance uncertainty in the dynamics model, such as the ground reaction force. The self-learning scheme updates the parameters of the EMG model so that it can adapt to the time variant nature. In summary, the estimator of the human intended torque switches between the dynamics model and the EMG model in the swing phase and in the stance phase, respectively, so the most accurate estimate of the two models can be always used for the assisting. With the estimation, we treat the human intention as the forced response of the estimated human intended torque exerting on a second-order linear system - the admittance interface. Finally, the sliding mode controller is used to overcome the uncertainties of modeling errors and disturbances.

To the best of our knowledge, no other papers have investigated the adaptive estimation of the EMG model via self-learning. Our self-learning exoskeleton uses the dynamics model to teach EMG model so that the EMG model can cover for the dynamics when needed. The hybrid scheme overcomes the insufficiency of using only a single model. Compared to [9], the dynamics model, identified offline, serves as the supervisor and teaches the EMG model online in this paper,

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whereas Cheng et al. use the Bayesian machines to combine the two models, which are both trained offline.

The paper is organized as follows. Section II gives the knee orthosis system and the modeling. In Section III, we describe the self-learning scheme and the sliding mode admittance control. In Section IV, we verify the performance of the proposed scheme in simulations and experiments, and the results are discussed. Finally, we give a short summary in Section VI.

II. Knee Orthosis System and Modeling

A. Exoskeleton System

The exoskeleton system comprises the knee orthosis system and the footswitch. The knee orthosis system is driven by a backdrivable spring torsion actuator (BTSA) [10]. The soft stiffness of the BTSA provides mechanically intrinsic safety and measures the torque between the human and the actuator. Fig. 1 shows the exploded view of the BTSA, and the specification of the BTSA is shown in Table I. The actuator, the output bevel gear, and the torsion spring are connected in serial. A potentiometer is installed to measure the knee angle via the belt transmission between the output joint and the input shaft. The deflection of the spring is measured as the difference between the potentiometer and the encoder of the motor, which can be used to calculate output torque via the Hooke's law. And the footswitch is used to detect the swing phase and the stance phase.

B. The Dynamics Model and the EMG Model

The dynamics model of the human-knee orthosis system is given by:

$$J\ddot{q} + B\dot{q} + Asign(\dot{q}) + M\sin(q) = \tau_E + \tau_h + \tau_g, \qquad (1)$$

where q is the angular position, J is the inertia, B is the viscous friction, A is the static friction, M is the gravity torque, τ_E is the external torque of the exoskeleton, τ_h is the external torque of the human muscle, and τ_g is the external torque of the ground reaction force, which is assumed to be zero during the swing phase. The parameters of the dynamics model are calibrated offline in the experiments.

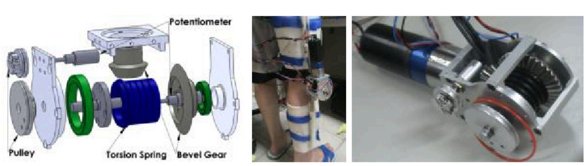


Fig. 1. Exploded view of the backdrivable torsion spring actuator, Knee orthosis, and Backdrivable torsion spring actuator

Table I specifications of the BTSA

Weight (including the motor)	835 g
Length*Width*Height	62x50x187 mm^3
Reduction Ratio of Bevel Gear	2:1
Reduction Ratio of Motor Gear Head	43:1
Stall Torque	87.5 Nm
No-Load Speed	404 deg/sec
Spring Stiffness	40 Nm/rad

*The input motor used in this design is a Faulhaber DC-micromotor 3863H024CR with gear head 38/2 S (43:1).

We use the linear combination of the filtered EMG signals, the flexor E_f and the extensor E_e, as the EMG model. That is,

$$\hat{\tau}_h = a_e E_e + a_f E_f + a_{bias}, \qquad (2)$$

where a_e, a_f, a_{bias} are the unknown parameters to be identified. Although more sophisticated EMG models are possible, in our experience, the linear model suffices to predict the human intended torque.

C. Offline System Identification

In this section, we describe how the unknown coefficients in (1) and (2) are identified offline. Unlike the EMG model, the dynamics model identified offline can predict with high accuracy as long as no unmodeled disturbance comes in, since it is time invariant. The EMG model, however, can only be approximated locally due to the unmodeled uncertainties and the slow variation of the parameters. Therefore, the identification of the dynamics model is carried offline, whereas the EMG model learns online from the dynamics model in the swing phase with the initial parameters identified offline.

The task for the identification of the dynamics model is shown in Fig. 2 (a). During this task, the user needs to relax totally such that τ_h can be approximated to be zero. The system model becomes

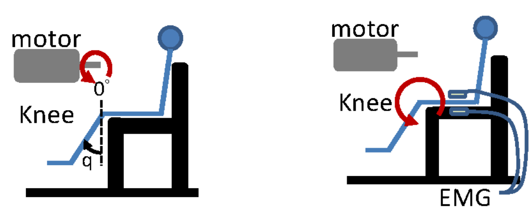
$$\tau_E = J\ddot{q} + B\dot{q} + Asign(\dot{q}) + M\sin(q) \qquad (3)$$

The stimulus signals are the sinusoidal position trajectories of q with different frequencies. The filtered angular position q, the angular velocity $\dot{q}$, the angular acceleration $\ddot{q}$, and the torque τ_E are collected to identify the unknowns by the ordinary linear regression.

The task for the EMG model identification is shown in Fig. 2 (b). During this task, the user tries to exercise his leg, while the knee angle is fixed to be a constant position by the position controller. The system model becomes

$$-\tau_E = \tau_h = a_{e\_0} E_e + a_{f\_0} E_f + a_{bias\_0}, \qquad (4)$$

and the identified parameters $\boldsymbol{\theta}_0 = [a_{e\_0}, a_{f\_0}, a_{bias\_0}]$ are used as the initial condition for the online learning.



(a) dynamics model identification (b) EMG model identification

Fig. 2. Offline dynamics and EMG model identification

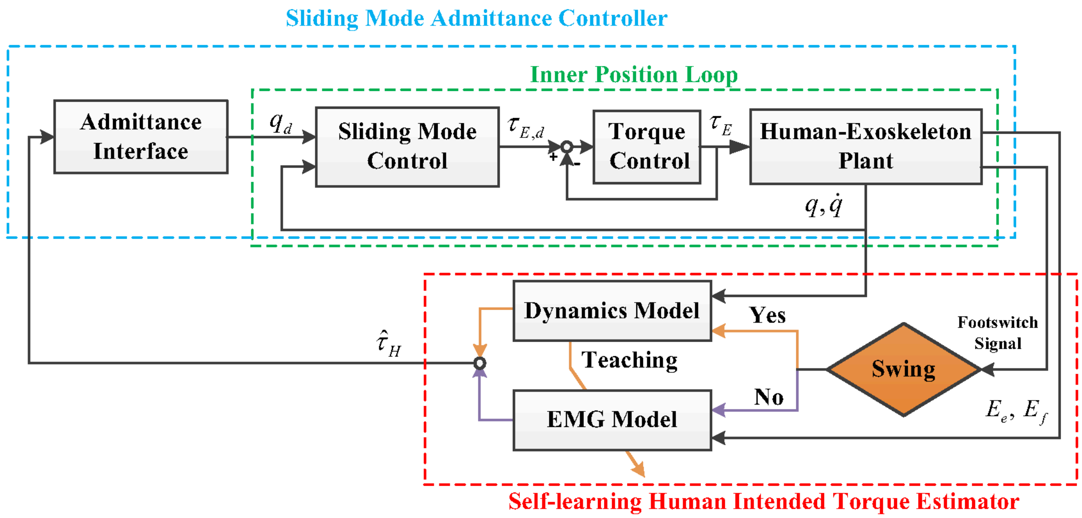


Fig. 3. The self-learning control scheme of the exoskeleton system

III. Self-Learning Scheme and Sliding Mode Admittance Control

The general idea of the exoskeleton control is to exert the force required by the operator. We believe that human reduces the muscle force when feeling the positive feedback. Therefore, the exoskeleton can assist the operator and reduces the payloads by providing the desired force.

We classify the walking phases into the swing phase and the stance phase, and the controller switches in between according to the footswitch. In the swing phase, the dynamics model identified offline is used to estimate the human intended torque, and to teach the EMG model; in the stance phase, the EMG model, becomes the estimator. In both phases, the admittance interface transfers the estimated torque of either the dynamics model or the EMG model to the position command, and effectively filters the discontinuities of the switching. Therefore, the reference position trajectory for the inner position controller is continuously differentiable, and is tracked by the sliding mode controller in the inner position control loop. In summary, the exoskeleton system consists of two control loops. The upper control loop estimates the human intention and learns online; the lower control loop tracks the reference trajectory robustly by the sliding mode controller, as shown in Fig. 3.

A. Self-learning Scheme

Self-learning, also called self-training, is a technique for semi-supervised learning. Semi-supervised learning is a methodology of machine learning and used in the scenario where accessing the labeled data is hard or expensive. The semi-supervised learning machine takes into account both the labeled and the unlabeled data to improve the performance. In the supervised step, the machine is first trained with the small amount of labeled data, and then it is used to predict the unlabeled data. During the unsupervised process, the machine labels parts of the confident unlabeled data and retrains. We found the mechanism very suitable for the exoskeleton. In our case, the exoskeleton learns offline with the data collected from the strictly controlled experiments, which is time consuming if large amount of data are in need. In the unsupervised step, the machine labels the unlabeled data by the dynamics model, and the newly labeled data are used to teach the EMG model. In this design, the exoskeleton system consists of a weak learner, the EMG model, and a strong learner, the dynamics model. In spite of the ability, the strong learner can only be used in the restricted domain, and therefore the strong learner has to teach the weak learner to compensate the deficits. That is, in the swing phase, the dynamics model teaches the EMG model, since it is accurate in absence of external disturbances. And then the EMG model takes over when the dynamics model fails. We detail the process as follows.

In the swing phase, using (1) with the parameters identified offline and τ_E measured by the BTSA, the dynamics model can estimate the human intended torque. The estimation is used to teach the EMG model by the following adaptive law with the initial parameters identified offline in (4). From (1) and (2), we have

$$\begin{aligned} &J\ddot{q} + B\dot{q} + A\,\mathrm{sign}(\dot{q}) + M\sin(q) - \tau_E \\ &\approx a_e E_e + a_f E_f + a_{bias} \end{aligned}, \tag{5}$$

so the human intended torque can be measured by the dynamics model with

$$z := \frac{[J\ddot{q} + B\dot{q} + A\,\mathrm{sign}(\dot{q}) + M\sin(q) - \tau_E]}{\Lambda(s)} = \boldsymbol{\theta}^{*T}\boldsymbol{\Phi}, \tag{6}$$

where $\boldsymbol{\theta}^{*T} = \left[a_e^*,\ a_f^*, a_{bias}^*\right]^T$ is the optimal parameter with respect to the L_2-norm error,

$$\boldsymbol{\Phi} = \left[\Lambda(s)^{-1}E_e,\ \Lambda(s)^{-1}E_f,\ \Lambda(s)^{-1}\right]^T$$

is the regressor vector, and, with the abuse of notation, $\Lambda(s)$ denotes Hurwitz system, which is chosen as the Butterworth low-pass filter in the experiments, and s is the variable of Laplace transform. Let the empirical estimation be

$$\hat{z} = \hat{\boldsymbol{\theta}}^T \boldsymbol{\Phi}, \qquad (7)$$

where $\hat{\boldsymbol{\theta}} = \left[\hat{a}_e,\ \hat{a}_f,\ \hat{a}_{bias}\right]^T$ is estimated parameters. The error between the measurement and estimation is given as

$$\varepsilon = \frac{z - \hat{z}}{m_s^2} = \frac{\tilde{\boldsymbol{\theta}}^T \boldsymbol{\Phi}}{m_s^2}, \qquad (8)$$

where $\tilde{\boldsymbol{\theta}} = \boldsymbol{\theta} - \hat{\boldsymbol{\theta}}$,and m_s^2 is the normalization factor such that $\boldsymbol{\Phi} / m_s^2 < \infty$ .Considering the cost function $J(\boldsymbol{\theta})$,

$$J(\boldsymbol{\theta}) = \frac{\varepsilon^2 m_s^2}{2} = \frac{(\tilde{\boldsymbol{\theta}}^T \boldsymbol{\Phi})^2}{2m_s^2}, \qquad (9)$$

the adaptive law is given by taking the negative gradient, that is

$$\dot{\boldsymbol{\theta}} = -\gamma \nabla J(\boldsymbol{\theta}) = \gamma \varepsilon \boldsymbol{\Phi},\ \boldsymbol{\theta}(0) = \boldsymbol{\theta}_0, \qquad (10)$$

$$\nabla J(\boldsymbol{\theta}) = -\frac{(z - \boldsymbol{\theta}^T \boldsymbol{\Phi})}{m_s^2} \boldsymbol{\Phi} = -\varepsilon \boldsymbol{\Phi}, \qquad (11)$$

where $\gamma > 0$ is the learning rate. Let

$$V := \frac{1}{2\gamma} \left\| \tilde{\boldsymbol{\theta}} \right\|_{l_2}^2 \geq 0 \qquad (12)$$

be the Lyapunov function. The adaptive law is stable since

$$\dot{V} = \frac{\tilde{\boldsymbol{\theta}}^T}{\gamma} \frac{d\tilde{\boldsymbol{\theta}}}{dt} = -\frac{(\tilde{\boldsymbol{\theta}}^T \boldsymbol{\Phi})^2}{m_s^2} = -\varepsilon^2 m_s^2 \leq 0. \qquad (13)$$

B. Sliding Mode Admittance Control

The sliding mode admittance control consists of the admittance interface, the sliding mode controller, and the PD torque controller. The main advantages of sliding mode admittance control are that the admittance interface in fact acts as a low-pass filter, so the tracking position trajectory is smoother than the estimated human intended torque, and that the sliding mode controller can handle the uncertainty of the modeling errors and the disturbance robustly. Compared to the methods [1, 2, 7, 8] that compensates only impedance of the dynamics, the main difference here is that the human intended torque is also considered, and therefore the assistance is more direct and more precise.

The admittance is used to model the relationship between the human intended force and the relative angular position,

$$M_h(\ddot{q}_d - \ddot{q}) + B_h(\dot{q}_d - \dot{q}) + D_h(q_d - q) = \hat{\tau}_h \qquad (14)$$

where M_h , B_h , and D_h are user-specific dynamics parameters, q_d is the desired trajectory of the output link, q is the current position, and $\hat{\tau}_h$ is the estimated human intended torque. The desired trajectory is forced response of the second-order system, so it is continuously differentiable. Note that (14) is the compliance control in the impedance control literatures, so exoskeleton follows smoothly regardless of the discontinuities in the estimated human intended torque.

With the desired trajectory from the admittance interface, the sliding mode controller uses the sliding surface to generate the torque command, which is tracked by the PD torque controller.

The nominal model of the human-exoskeleton system can be modeled as

$$\ddot{q} = \hat{f} + \hat{J}^{-1} \tau_E + \delta \qquad (15)$$

$$\hat{f} = -\frac{1}{\hat{J}}[\hat{B}\dot{q} - \hat{M}\sin(q) + \hat{\tau}_h] \qquad (16)$$

where $\hat{\tau}_h$ is the estimated human intended torque, $\hat{J}$, $\hat{B}$, $\hat{M}$ are the estimated parameters, $\|\delta\|_\infty < D$ is contribution of all the modeling uncertainties and the disturbances and is bounded by some constant $D < \infty$. Notice that we include the static friction term $Asign(\dot{q})$ in δ so that the nominal plant (15) is bounded and continuous. In order to let the system track $q \approx q_d$, the sliding surface $S = 0$ is defined as (17)

$$S = \dot{\tilde{q}} + \lambda \tilde{q} \qquad (17)$$

$$\dot{S} = \ddot{q} - \ddot{q}_d + \lambda \dot{\tilde{q}} = f + \hat{J}^{-1} \tau_E + \delta - \ddot{q}_d + \lambda \dot{\tilde{q}}, \qquad (18)$$

where $\tilde{q} = q - q_d$ and $\lambda > 0$. Assuming $\hat{J}(f + \delta - \ddot{q}_d + \lambda \dot{\tilde{q}}) < \infty$, to achieve $\dot{S} = 0$, we set

$$\overline{\tau}_E := \hat{J}(-f + \ddot{q}_d - \lambda \dot{\tilde{q}}). \qquad (19)$$

To satisfy the sliding condition under the uncertainty d , the torque reference is designed as (27).

$$\tau_{E,d} := \overline{\tau}_E - \sigma \hat{J} \text{sat}(S / \beta), \qquad (20)$$

which is the torque reference for the inner torque control loop, where $\sigma > 0$,

$$\text{sat}(x) = \begin{cases} x, & \text{if } |x| \leq 1 \\ \text{sgn}(x), & \text{if } |x| > 1 \end{cases},$$

$\text{sgn}(\cdot) = \{\pm 1, 0\}$ denotes the sign function, and $\beta > 0$ is the thickness of the boundary layer. Choose the Lyapunov function as

$$V_1 = \frac{1}{2} S^2 \geq 0 \qquad (21)$$

Set $\sigma = \eta + D$ with $\eta > 0$, we can show that for $|S / \varepsilon| > 1$

$$\dot{V}_1 = \frac{1}{2} \dot{S} \cdot S = [\delta - \sigma \text{sgn}(S)] S < -\eta |S| < 0. \qquad (22)$$

Therefore, $\{S \mid |S / \beta| \leq 1\}$ is positively invariant. Inside the boundary layer, take

$$V_2 = \frac{1}{2} \tilde{q}^2 \qquad (23)$$

and we have

$$\dot{V}_2 = \tilde{q}(S - \lambda\tilde{q}) < -\lambda(1-\theta)\tilde{q}^2 < 0 \quad (24)$$

for $|\tilde{q}| \geq (\theta\lambda)^{-1}|S|$, where $0 < \theta < 1$. The error $\tilde{q}$ is ultimately bounded in the ball $|\tilde{q}| < (\theta\lambda)^{-1}|S|$.

IV. Experimental Results and Discussion

A. Simulation Results

We use the second-order human muscle model proposed in [10] to simulate the effect of the exoskeleton. Assuming human is an ideal controller, and the control objective is to track a sinusoidal position trajectory. In the simulation, we assume the estimated human intended torque is known. Fig. 4 (a) shows human applied torque and the interaction force due to the mechanical impedance of the exoskeleton and the human body during the tracking; Fig. 4 (b) shows the result with the assistance of the exoskeleton. With the assistive control, the human applied torque decreases significantly by a factor of 4, and the torque error in the sliding mode control converges to the boundary layer exponentially, despite little chattering along the boundary. The simulation results prove the effect of the sliding mode admittance controller.

B. Experimental Results

In the experiments, the subject is a healthy 32-year-old male, and he is asked to climb the stairs up and down with the BTSA knee othosis. Before the task starts, the exoskeleton system is calibrated offline according to Section II. During the task, the self-learning exoskeleton estimates the human intended torque with the dynamics model and the EMG model in the swing phase and the stance phase, respectively. And then the estimation is used for the sliding mode admittance controller. All the EMG signals are rectified, filtered by the Kalman filter [11] and offset such that the EMG signal is zero when muscles are totally relaxed. Fig. 5 shows how the EMG model learns during the task with the initial parameters identified offline. In each swing phase, the EMG model is updated to adapt to current condition, and the result shows the parameters of the EMG model is indeed time-variant. This is because to approximate the nonlinear model, the linear model is only valid locally, and the electric resistance between the electrodes and the operator changes with time due to sweats and slipping. Therefore, it is necessary to learn the EMG model online.

To compare the self-learning estimator and the single model approach, the estimations are shown in Fig. 6 (a). Combining the two models, the self-learning estimator switches between the two models according to the gait phase. In the swing phase, the EMG model tries to learn from the dynamics model, so it can encounter the uncertainties in the stance phase. We observe that the dynamics model overestimate the human intended torque in the stance phase, because it includes the torques from the disturbance and the exoskeleton. Indeed, when climbing, the hamstrings and the quadriceps exert the most in the swing phase and relax in the stance phase. This accounts for the estimation of the EMG model. Therefore, if we use the dynamics model in all the phases, the operator might be easily injured by the large forces

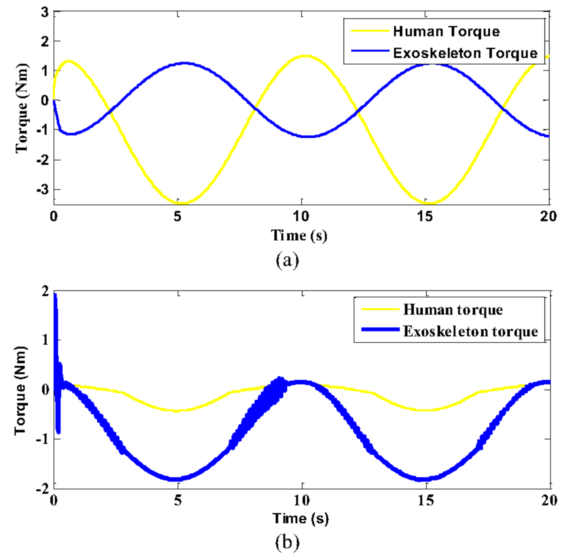


Fig. 4. The results of the sliding mode admittance controller (a) without the assistive control (b) with the assistive control.

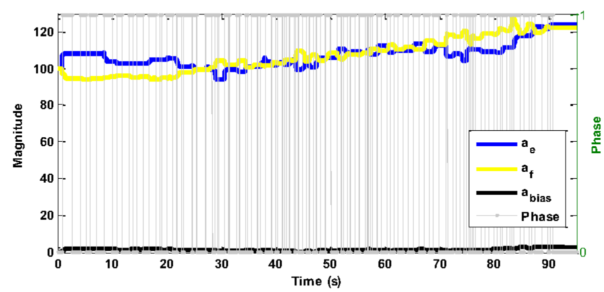


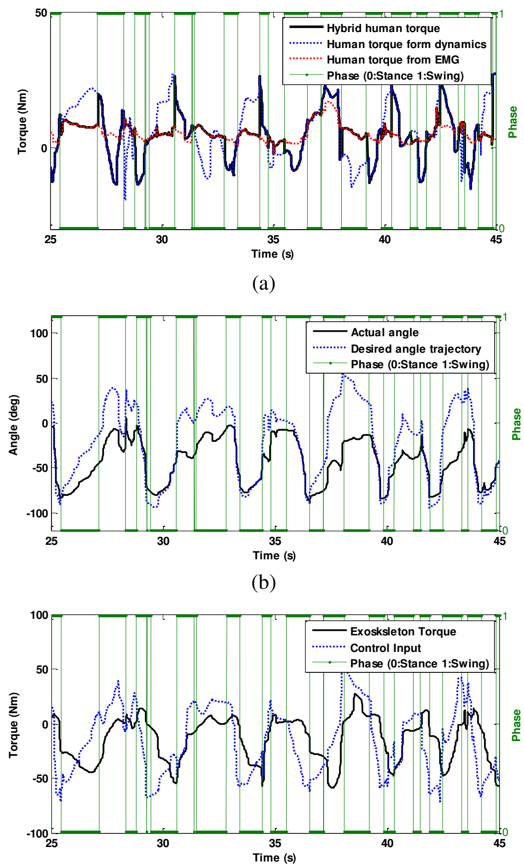
Fig. 5. The parameters of the EMG model.

provided by the exoskeleton in the stance phase, since it amplifies not only the human intended torque but also the torque due to exogenous disturbance. In this case, the operator has to exert large forces to compensate the disturbance, which is the major defect of most of the exoskeleton with only the dynamics model.

Fig. 6 (b) shows the reference position from the admittance interface. Despite the discontinuity of the torque estimation in Fig. 6 (a), the desired position trajectory is continuously differentiable owing to the second-order system. The torques are shown in Fig. 6(c).

V. Discussions

In the implementation, the sliding mode control plays an important figure. As discussed, the thickness of the boundary layer trades off the magnitude of the chattering and the tracking error. In contrast to the conventional sliding mode controller used in the tracking, we design our sliding mode controller with large boundary layer. Augmented on human, the success of an assistive controller relies more on the smoothness, the phase, and the direction of the assisting torque rather than the actual value of the supporting force and



(a)

(b)

(c)

Fig. 6. (a) The self-learning estimator, the dynamics model, and the EMG model. (b) The actual angle and the desired angle generated from admittance interface. (c) The torque command of the sliding mode controller and exoskeleton torque.

the position tracking error. With such knowledge, the boundary layer should be large as long as it pushes the exoskeleton from large tracking errors; inside the boundary, the sliding mode control is actually a proportional feedback controller to provide smooth assisting.

In the experiments, we observe that the optimal parameters of the admittance interface vary with the configurations and the tasks. It is interesting that human expect different impedance with various poses. We suggest identify the task-dependent impedance and use the gain scheduling technique to control the impedance system in the future works. Also, the learning rate affects the performance of the EMG model very much. With small learning rate, the EMG model cannot learn fast enough within the short swing phase, while the learning becomes more unstable when large learning rate is used. Therefore, the learning rate trades off the performance and the stability. We hope this can be addressed by incorporating the adaptive learning rate and the Hessian matrix. Finally, we are considering whether the robust control approach is suitable in the application of exoskeleton. Most of the robust control uses finite bounds for the disturbances and the uncertainty, and forces the tracking error to stay within some bounded domain. On the other hand, the interaction with human does not emphasize the absolute error. Indeed, only the bandwidth and smoothness do matter. In our experiences, human seems to be able to adapt to the errors easily as long as the bandwidth is limited.

VI. Conclusion

In this paper, we propose the self-learning scheme with the sliding mode admittance controller for the assistive exoskeleton system. The self-learning scheme combines both the dynamics model and the EMG model to achieve better performance. In the swing phase, the dynamics model teaches the EMG model, so that the estimated human intended torque can tolerate the disturbance uncertainties in the stance phase. Together, the estimator uses the dynamics model in the swing phase and the updated EMG in the stance phase. With the estimated human intended torque, the sliding mode admittance controller assists the operator robustly. In the future works, we want to address the issue of pose-dependent desired impedance and design a more sophisticated self-learning scheme.

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