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Development of An Adaptive Iterative Learning Controller With Sensorless Force Estimator for The Hip-type Exoskeleton

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Abstract— **Nowadays industrial loads lifting still heavily relies on manual operation. Long-term lifting job can hugely increase low back strains and even cause lumbar diseases. With the rapid development of exoskeleton systems, it is essential to develop a hip-type exoskeleton for the porters. This paper proposes a modified adaptive iterative learning-based control algorithm with a sensorless force estimator. The advantage of this algorithm is that the exoskeleton joint can move precisely along the desired trajectory as well as generate an external assistance torque based on the force estimator while the wearer lifting the load. A hip-type exoskeleton device has been developed to evaluate the effectiveness of this algorithm. We carried out experiment works of bending and lifting heavy loads. Experimental results show that when choosing the IEMG of LES as the evaluation criteria, our exoskeleton device with the proposed control algorithm can significantly reduce the strain force of the wearer's lumbar over 40% when they lift heavy loads. Thus it can improve the work efficiency of wearers and reduce their risk of lumbar diseases.**

Index Terms— **Iterative Learning Control, Hip-type Exoskeleton, Sensorless Force Estimation**

I. Introduction

Recently, with the rapid development of robotics, traditional manual operations are being widely replaced by automatic machines. In spite of this, some unique working places, for instance, the express delivery industry, the construction industry, and the civil aviation industry, on account of its' costly and inflexible trait, automatic equipment can't up to the job on these occasions. According to the data from National Bureau of Statistics of China, thanks to the development of e-commerce, in 2018, 50.71 billion express parcel were delivered to consumers in China, which increased by 26.6 percent compared with 2017 [1]. Long-term handling heavy loads give rise to a high probability of irreversible strain to the workers' lumbar muscles and spinal, so far as to the incapacitation of workers.

To address this phenomenon, many institutions have conducted research in the civil- oriented, miniaturized, and motor driven lumbar support exoskeletons. Japanese company CYBERDYNE Inc. has developed a series of exoskeleton, the Hybrid Assistive Limb (HAL), and the Lumbar Type of HAL can provide additional Torque on the hip joint to pull the wearers up during they lifting loads [2]. In addition to the HAL (the Lumbar Type), many hip-type exoskeletons have emerged in recent years, such as ATOUN's MODEL A by ATOUN (2017) [3], Muscle Suit by Innophys (2014) [4], 4-DoFs Wearable Hip Exoskeleton by North Carolina State University (2017) [5], and Waist Exoskeleton by SIAT (2017) [6].

Given their interaction with the wearers, control of exoskeletons, however, is still an unfinished building. With its self-evident properties and simple implementation, impedance control is frequently employed in the field of exoskeleton control. [7] details an impedance control strategy estimated using the virtual impedance of the exoskeleton with interaction torque between the wearer's joint and the exoskeleton, which is identified by a series-elastic actuator. [8] propose a novel control algorithm for a lower-limb assistive exoskeleton based on the virtual mechanical impedance of the wearer's limb. In [9] through surface electromyography signals of the wearer to modify their dynamic impedance parameters, then use an adaptive neural network to control the exoskeleton tracking reference trajectory.

Although the impedance controller works well in some spcific environments. Unfortunately, exoskeletons are intended for operating by different wearers, these control methods do not consider the time-varying capabilities of different wearers and therefore control parameters may not be intervened rapidly. Besides, to obtain the impedance parameters of the human body auxiliary sensors are needed, which make the complexity of the exoskeleton system skyrocketing.

Technically, the hip-type exoskeleton device consists of two 1-DOF joints, and do tracking of repetitive tasks during the working. In the past decades, iterative learning control (ILC) has been well known because of its effective performance in dealing with repeated tracking control of the robot. [10] proposed a standard Lyapunov based method to devise an adaptive controller for the uncertain manipulators,

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in which uncertain parameters are estimated along with the repetitive iterations. However, this method requires that the unknown system parameters be invariable. Based on the above standard technique of adaptive controller designing, in [11], a simple ILC scheme consists of a PD term and an additional iterative term for trajectories tracking of robot manipulators has been presented.

In this paper, we introduce a PD-type Adaptive Iterative Learning Controller (AILC), which utilizes a sensorless torque estimation algorithm to determine the inputs of the exoskeleton and the unknown interaction force between the exoskeleton and the wearer. We solve this problem by adding them with the states before the exoskeleton provides the wearer an external assisted torque with the adjustable bounded position and velocity errors. The adaptive torque estimator modified the estimation of the unmodeled inputs by updates them with a Lyapunov based adaptation law. These estimated states will eventually be used to update the control inputs of the exoskeleton and make it move along the desired trajectory and velocity.

This paper is organized as follows. Section II derives the iterative learning control method and its implementation results. Section III details the load experiments of the hip-type exoskeleton and the results. Finally, the conclusions of this work are presented in section IV.

II. METHOD

A. Sensorless Force Estimation

Using the Lagrangian mechanics, we can present the robot dynamics by

$$M(q)\ddot{q}+C(q,\dot{q})\dot{q}+G(q)=\tau+d, \tag{1}$$

where q,$\dot{q}$,$\ddot{q}$ are vectors of the joint position, joint velocity and joint acceleration, M is the inertial matrix,$C(q,\dot{q})\dot{q}$ represents the Coriolis and centrifugal forces, $G(q)$ is the component force vector resulting from the gravity, τ_r is a vector of torques provided by actuators, d is the disturbance vector of inputs.

The ever-present interaction forces make the most significant difference between an exoskeleton and an ordinary robot; these interaction forces and the unmodeled system dynamics can be regarded as disturbances in the process of exoskeleton control. Torque and force sensors are commonly used to obtain the interaction force between robot and human in real time, the introduction of measuring elements increases the cost of robot development and will inevitably cause intrusion into the system. In this paper, we selected a modified sensorless force estimator proposed in [12], which employs a modified Kalman Filter with Lyapunov based stability analysis. The estimated disturbances $d=\tau_d$ can be divided into interaction forces τ_I and the unmodeled system dynamics τ_m, can be formulated as

$$\tau_d=\tau_I+\tau_m. \tag{2}$$

Applying this definition, we can rewrite the exoskeleton dynamics as

$$M(q)\ddot{q}+C(q,\dot{q})\dot{q}+G(q)=\tau_r+\tau_d. \tag{3}$$

The above nonlinear process dynamics can be given by the stochastic state-space model as

$$\begin{array}{l}\dot{x}=Fx+G(\tau_r+\tau_d-g(x))+w\\ y=Hx+v\end{array}, \tag{4}$$

where F, G, H, D are matrices constituting the estimated nonlinear model. $x=\left(q^T,\dot{q}^T\right)^T$ is the state vector. y is the measurement vector. τ_r is the input vector. w and v are the system process noise and measurement noise with covariances equal to Σ_w and Σ_v. The estimations of the states ($\hat{x}$), measurements ($\hat{y}$) and symmetric positive definite error covariance matrix (P) estimated with modified KF can be given by

$$\begin{array}{l}\dot{\hat{x}}=F\hat{x}+G(\tau_r+\hat{\tau}_d-g(\hat{x}))-K(\hat{y}-y)\\ \hat{y}=H\hat{x}\\ \dot{P}=FP+PF^T+\Sigma_w-PG^TR^{-1}GP\end{array}, \tag{5}$$

where $\hat{\tau}_d$ is the estimated disturbance input vector. $K=PH^TR^{-1}$ is the Kalman gain according to [12], where Σ_w is the residual covariance matrix. We can define the estimated errors of x and τ_d as $e=\hat{x}-x$ and $e_d=\hat{\tau}_d-\tau_d$, $\bar{e}$ and $\bar{e}_d$ represent the moving average of e and e_d . According to equation 4 and 5, the moving average of system dynamics can be obtained as

$$\dot{\bar{e}}=(F-KH)\bar{e}+G\bar{e}_d. \tag{6}$$

Using the above definition, we can introduce the Lyapunov function

$$V=\frac{1}{2}\bar{e}^T\Psi\bar{e}+\frac{1}{2}\bar{e}_d^T\Gamma^{-1}\bar{e}_d, \tag{7}$$

where Ψ and Γ are user-elected symmetric positive definite constant weighting matrices. Then we compute the time derivative of V and substitute equation 9 into, we can obtain

$$\dot{V}=\bar{e}^T\Psi\left(F-PH^TR^{-1}H\right)\bar{e}+\bar{e}_d^T\left(G^T\Psi\bar{e}+\Gamma^{-1}\dot{\bar{e}}_d\right), \tag{8}$$

to make $\dot{V}$ be negative semi-definite, we select the residual covariance R and adaption law of the estimated force $\hat{\tau}_d$ to be

$$\begin{array}{l}R=\left(\left(H^T\right)^{-1}P^{-1}(F+\alpha I)H^{-1}\right)^{-1}\\ \dot{\hat{\tau}}_d=-\Gamma G^T\Psi H^{-1}(\hat{y}-y)\end{array}, \tag{9}$$

where α is a positive constant, by setting $\dot{\tau}_d=0$ and inserting equation 9 into 8 we can get

$$\dot{V}=-\bar{e}^T\alpha\Psi\bar{e}, \tag{10}$$

it is clearly negative semi-definite, hence, the system is Lyapunov stable.

With equation (10), a conclusion can be recognized that V is monotonically decreasing, which implies that V is bounded, we can derive that $V(t) \leq V(0)$, then $V(\infty)$ is existing and bounded. With the definition of V, we can get

$$\int_0^{\infty} \bar{e}(t)^T \bar{e}(t)\, dt \leq \frac{1}{\lambda_{\max}} \left(V(0) - V(\infty)\right) < \infty, \tag{11}$$

where $\lambda_{\max}$ is the maximum eigenvalue of matrix $\Psi\left(F - PH^T R^{-1} H\right)$, so it can be noted that $\bar{e}$ and $\bar{e}_d$ are also bounded.

B. Adaptive Iterative Learning Controller

By introducing the iteration number k, equation 1 can be extended to

$$M(q_k)\ddot{q}_k + C(q_k, \dot{q}_k)\dot{q}_k + G(q_k) = \tau_{r,k} + \tau_{d,k}. \tag{12}$$

The joint position q_k and joint velocity $\dot{q}_k$ can be obtained by the sensor and as feedback for the controller, the objective is to obtain a bounded input control signal $\tau_{r,k}$ through the boundness of these feedback signals, and q_k will eventually converge to the desired trajectory for all $t \in [0,T]$ as k approaches infinity.

To make the controller converge, the following assumptions should be introduced, the desired trajectory q_d and its first and second-time derivatives $\dot{q}_d$, $\ddot{q}_d$,as well as the input disturbances $\tau_{d,k}$ are all bounded $\forall t \in [0,T]$.

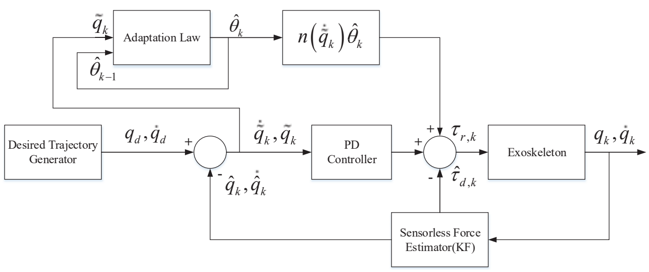

Fig. 1. Block diagram of PD-type Adaptive Iterative Learning Controller with sensorless force estimator

Let us make the following control law for the exoskeleton dynamics (Fig. 1)

$$\tau_{r,k}(t) = K_P \tilde{q}_k(t) + K_D \dot{\tilde{q}}_k(t) + \eta\left(\dot{\tilde{q}}_k(t)\right)\hat{\theta}_k(t) - \hat{\tau}_{d,k}(t), \tag{13}$$

with adaption law

$$\hat{\theta}_k(t) = \hat{\theta}_{k-1}(t) + \Gamma\eta^T\left(\dot{\tilde{q}}_k(t)\right)\dot{\tilde{q}}_k(t), \tag{14}$$

where the parameters are defined as $\tilde{q}_k(t) = q_k(t) - q_d(t)$ and $\dot{\tilde{q}}_k(t) = \dot{q}_k(t) - \dot{q}_d(t)$. K_P and K_D donate the proportional and derivative symmetric positive definite gain matrices of the PD controller, t is the time. The iterative variables $\eta\left(\dot{\tilde{q}}_k(t)\right)$ can be defined as $\eta\left(\dot{\tilde{q}}_k(t)\right) = \left[\begin{array}{cc} \dot{\tilde{q}}_k(t) & \operatorname{sgn}\left(\dot{\tilde{q}}_k(t)\right) \end{array}\right]$ where $\operatorname{sgn}\left(\dot{\tilde{q}}_k(t)\right)$ applying the signum function value with $\dot{\tilde{q}}_k(t)$. The proof of this statement can be found in [13].

C. Simulation

A simple model of the hip-type exoskeleton is shown in Fig. 2, θ represents the angle between the trunk and thigh of the wear. According to [14], the change of θ during human lifting movement can be approximated by a fifth power function as

$$\theta = at^5 + bt^4 + ct^3 + d, \tag{15}$$

where time t is within the interval $[0,t_{end}]$. The coefficients a, b, c and d can be calculated by the boundary conditions where $\dot{\theta}(0)$, $\ddot{\theta}(0)$, $\dot{\theta}(t_{end})$,$\ddot{\theta}(t_{end})$, all equal zero and the initial value of θ equal d, where the function of angular velocity can also be simply determined as $\dot{\theta} = 5at^4 + 4bt^3 + 3ct^2$ and the angular acceleration function as $\ddot{\theta} = 20at^3 + 12bt^2 + 6ct$.

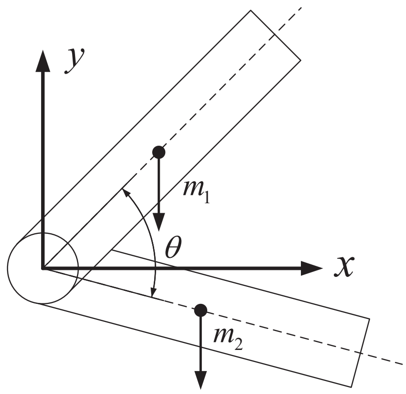

Fig. 2. A simple model of hip exoskeleton

We set θ to 180° when the wearers standing upright with the exoskeleton, the starting position for stooping to lift heavy loads can be set to 100° according to experience, convert the angles into radian can be expressed as $\theta \in \left(\begin{array}{cc} \frac{5}{9}\pi, & \pi \end{array}\right)$, as initial conditions, it can be substituted into equation 15 to determine the coefficients and obtain the desired trajectory and desired angular velocity of the exoskeleton. The results obtained by the Matlab-Simulink of these data are shown in Fig. 3 to 6. Applying the control described in equations (13) and (14), with $K_p = K_D = 15$ and $\Gamma = 10$.

As can be seen in Fig. 3, the maximum absolute tracking error decreases rapidly with the growth of iterations number, at the 20th iteration, the tracking error was almost zero. The same results can also be seen in Figs. 4 and 5. At the first iteration, both the angle and angular velocity were deviated

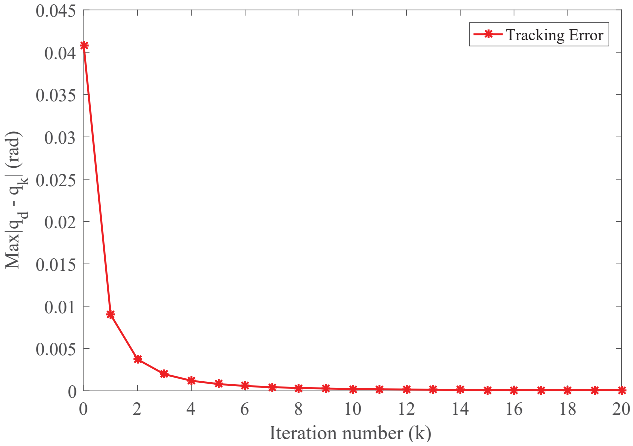

Fig. 3. Maximum absolute tracking error versus the number of iterations for the exoskelton

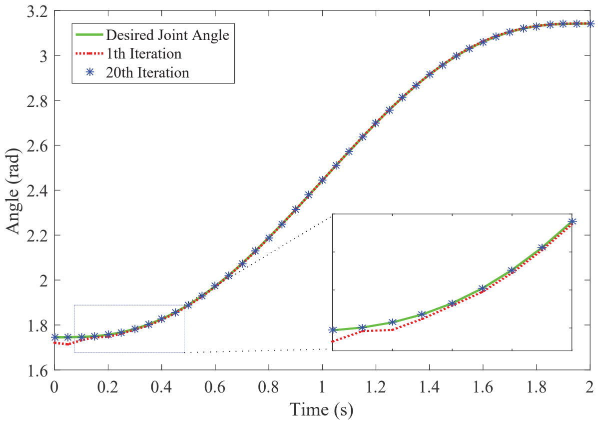

Fig. 4. Desired and actual trajectories at the first and 20th iteration

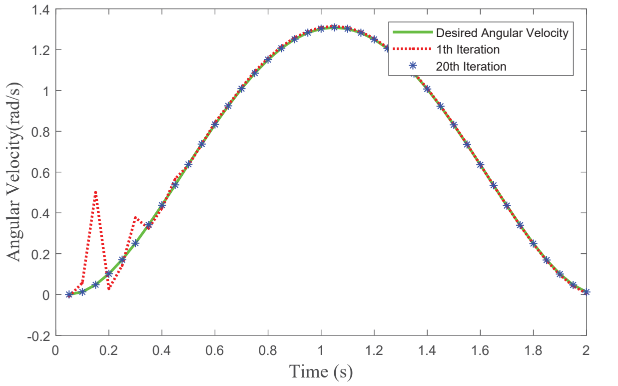

Fig. 5. Desired and actual angular velocities at the first and 20th iteration

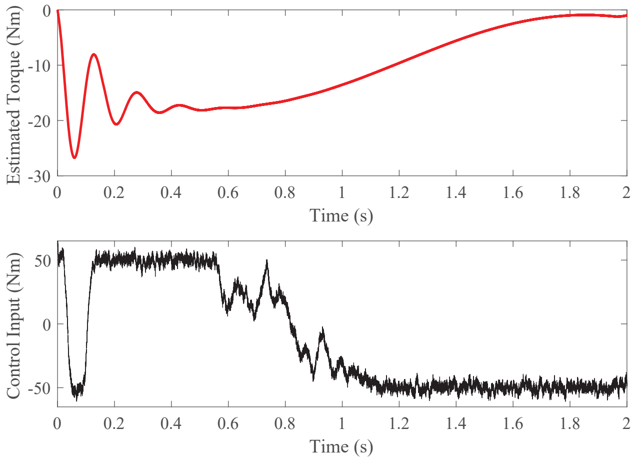

Fig. 6. The Estimated Interaction Torque and Control action for the exoskeleton after 20 iterations

from the desired values to some extent, after 20 iterations, the actual trajectory was consistent with the desired trajectory.

Fig. 6 showed the input of the controller, namely the output torque of the motor and the estimated torque between the exoskeleton and wear. The controller input appeared first positive and then negative that is consistent with the working process of the exoskeleton, which accelerates first and then decelerates. Since the maximum output torque of the exoskeleton experimental device is 60Nm, the threshold value input in the simulation is set as 55Nm; the simulation results also indicated this setting. The estimated interaction torque was always negative, which indicated that under this control algorithm, the exoskeleton would continue to assist the wearers during their lifting of heavy loads.

III. Experiments And Results

The research [15] has shown that dozens of lumbar muscles are involved in, when the human body bending to lift a heavy load, surface electromyographic signals (sEMG) describe the intensity of activity of the corresponding muscles. By measuring the amplitude of sEMG in the process of human movement and calculating their integral value, we can obtain the work condition of human muscles. The lumbar erector spinae (LES) plays a decisive role in the process of bending, in this work we will evaluate the assistance efficiency of the exoskeleton by measuring and calculating the integral sEMG value (IEMG) of LES of experimental volunteers before and after they wearing the exoskeleton, which also reflects the effect of the control strategy.

A. Experiment Setup

The Surface EMG Sensor (SX230) of Biometrics Ltd is an active sensor with the amplifier's input impedance over 10,000,00 M Ohms, pairing it with the data acquisition product the DataLOG (MWX8) [16], can obtain and display surface EMG data accurately (Fig. 7).

Fig. 7. Surface EMG Sensor (SX230), DataLOG (MWX8) and the positions of Surface EMG Sensor on LES

The experiment involved ten healthy volunteers with no history of lumbar muscle problems, the statistical data of their age, height, and weight are shown in Table I. The Surface EMG Sensor should be attached to the skin of the muscle during the experiment, and the DataLOG enabled the data to be uploaded via Bluetooth to a PC. In our experiment, we only measured the electromyographic signals of the left and right LES; the positions of the Surface EMG Sensor are shown in Fig. 7.

TABLE I
THE STATISTICAL DATA OF THE AGE, HEIGHT AND WEIGHT OF THE VOLUNTEERS

	Minimum	Maximum	Medium
Age(years)	18	40	30
Height(cm)	165	187	176
Weight(kg)	62	88	75

B. Experiment Procedure

The experiment will be divided into two parts; the volunteers were asked to bend over and lift the loads with and without the exoskeleton. The box inclusive the load is initially empty, which means the load is 0 kg, as the experiment went on, the load would gradually increase by 5kg with equal weight intervals, until 25kg. Each volunteer lifted 6 levels of load with and without the exoskeleton each for times, there are 10 minutes' pauses for the volunteers between two liftings, so that the volunteers' lumbar muscles are fully rested. A total of 600 person-time liftings have been accomplished during the whole experiment. A volunteer with the exoskeleton experimental device is shown in Fig. 8. The exoskeleton experimental device is driven by two brushless dc motors with an output torque of 0.75 Nm, and each of the motor was decelerated by a gear box whose reduction ratio is 40:1. Ideally, the device's maximum output drive torque is 60Nm.

Fig. 8. The phase of bending to lift heavy loads and the standing posture with the exoskeleton experimental device

C. Results and Analysis

After filtering and other processing of sEMG signals, calculating their integral values IEMG within one lifting cycle, we define the assistance efficiency of the exoskeleton by the following formula,

$$E = 1 - \frac{I_{Exo}}{I}$$

where I_{Exo} is the IEMG of LES when the volunteer lift the loads with the exoskeleton experimental device, and I is the IEMG of LES when the volunteer lift the same loads without the exoskeleton. Fig. 9 and Fig. 10 described the amplitudes' Root Mean Square of sEMG, which are obtained from the experiment, respectively.

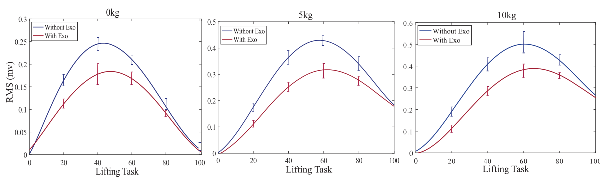

Fig. 9. The amplitudes' Root Mean Square of sEMG with loads from 0 kg to 10 kg

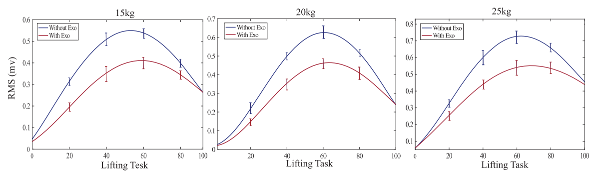

Fig. 10. The amplitudes' Root Mean Square of sEMG with loads from 15 kg to 25 kg

From Fig. 9 to Fig. 11, it is clear that with increasing of the loads the sEMG amplitudes and their integral values of LES were going to keep growing no matter the volunteers with or without the exoskeleton, but the value was significantly lower when the exoskeleton on. The data in Table II indicated that the IEMG decreased by almost the same amount, it's about 0.6 $mv*s$, after wearing the exoskeleton, which means that the exoskeleton can provide constant assistance to the wearer during each lifting. Therefore, numerically speaking,

TABLE II

THE STATISTICAL DATA OF IEMG AND THE ASSISTANCE EFFICIENCY OF EXOSKELETON UNDER DIFFERENT LOADS

	0kg	5kg	10kg	15kg	20kg	25kg
Without Exo (mv∗s)	0.38±0.032	0.49±0.03	0.56±0.04	0.69±0.037	0.79±0.041	0.86±0.036
With Exo (mv∗s)	0.13±0.02	0.22±0.025	0.27±0.021	0.39±0.022	0.47±0.03	0.51±0.022
Decrease (mv∗s)	0.25±0.052	0.27±0.055	0.29±0.061	0.3±0.059	0.32±0.071	0.35±0.058
Efficiency (%)	65.8±13.7	55.1±11.2	51.8±10.9	43.5±8.5	40.5±9.0	40.7±6.7

the assistance efficiency will decrease with the increase of the load, but it was all over 40% in this experiment, and the highest was 65.8%.

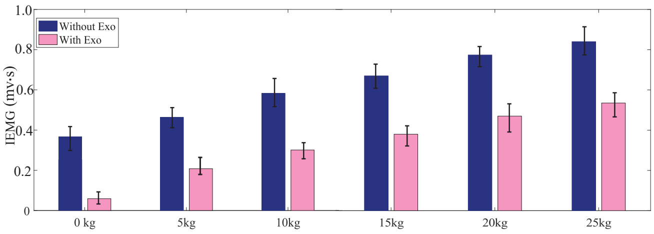

Fig. 11. The IEMGs of LES with loads from 0 kg to 25 kg

IV. CONCLUSION

In this paper, to control the exoskeleton and its wearers, a nonlinear and strongly coupled dynamic system with high uncertainty and it has a relatively repetitive trajectory. We propose an adaptive iterative learning control-based control algorithm, it is modified by a sensorless force estimator, which can estimate the interaction force between the wearer and the exoskeleton with the joint position and velocity of the exoskeleton. With this algorithm the exoskeleton can move perfectly along the desired trajectory and joint velocity, and give an external assistance torque while the wearer lifting the load. When choose the IEMG of LES as the evaluation criteria, this algorithm combined with the exoskeleton can significantly reduce the strain of the wearer's lumbar over 40% when they lift heavy objects, and improve the work efficiency of wearers and reduce their risk of lumbar diseases.The body parameters like weight and height of the exoskeleton operators are not considered in this work. Therefore, in future work, the proposed control algorithm in this paper will improve its adaptability on individual.

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