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Study on Resistance Training for Upper-Limb Rehabilitation Using an Exoskeleton Device

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Abstract –**Rehabilitation robotics has received more and more attention during the last decades, especially the exoskeleton device for the upper limb rehabilitation, but most of them are heavy and large. In our study, a light and wearable exoskeleton device was proposed, which can be used in home rehabilitation and it can also be used to implement passive and active training. In this paper, we proposed to perform the active rehabilitation based on the upper limb exoskeleton rehabilitation device (ULERD) with variable stiffness elastic actuators, which improves the safety for human-robot interaction and produces adjustable stiffness capacity and resistance training to meet the demand for safe active-passive elbow rehabilitation. It provides a wide approach for human machine interface (HMI) in which the device is non-backdrivable, and at the same time it is difficult to obtain the contact force information directly. The proposed method was verified by the experiments conducted under two conditions with passive DoFs unlocked and with passive DoFs locked during elbow flexion and extension performance. Each experiment has three level resistances provided to the user. The surface electromyography (sEMG) signals derived from biceps and triceps were used to evaluate the efficacy of this method in both experiments.**

I. Introduction

Stroke has been regarded as a leading cause of disability in the United States, which nearly 6.4 million Americans suffer[1]. These stroke patients usually require a task-specific therapy approach. In reality, budget constraints and therapist shortages limit a hand-to-hand therapy approach throughout the world, which overburden family and society [2]. The development of robotics makes it feasible to utilize rehabilitation robots to help stroke survivors to recover motor function. Especially upper limb rehabilitation robots are mainly differentiated into two types: exoskeleton and end-effector. In the end-effector type, the user grasps the end-effector (handle) of the robot to implement the rehabilitation, like the MIT-MAUNS, it has two degrees of freedom (DOF) for movement of performing task-oriented training, in which upper limbs including wrist, elbow and shoulder were involved[3], [4]. However, this kind of robots cannot target movements with specific joints of limbs. So many researchers focus on the exoskeleton strategy to solve this problem. One of the typical devices MEDARM, developed by the Canadian Institutes of Health Research (CIHR), used a cable driven curved track mechanism which can provide independent control [10]. ARMin [11] is also an exoskeleton device with six independent DoFs and one coupled DoF, which can effectively improve the motor function of the impaired arm for stroke patients [12]. However, the existing rehabilitation robots are not suitable for home-rehabilitation since they are so heavy and large. In our research, a novel light and portable exoskeleton device was designed for home-rehabilitation.

Rehabilitation robots as human-machine interaction(HMI) devices need to perform different training strategies in clinic to implement the rehabilitation tasks following evidence based medicine. Given the researches in neuro-rehabilitation [13-16], there are mainly three training strategies of physical rehabilitation: passive rehabilitation, active rehabilitation and bilateral rehabilitation [9], [17] and [18]. The robots for rehabilitation mentioned above not only can implement one or all kinds of these strategies, but also can adjust train level of these strategies according to different impairments. That is, the patients suffering weak stroke could perform passive rehabilitation strategy reasonably and the mild stroke survivors had better to get active rehabilitation, while those who suffer hemiparesis tend to perform bilateral rehabilitation. In our previous work, we focused on the implementation of passive rehabilitation and bilateral rehabilitation with ULERD and the active rehabilitation on elbow joint [19]. In this paper, we proposed to implement the active rehabilitation suitable for the ULERD. Given the difficulties to obtain the contact force between the user and device using the force sensor, sEMG signals are utilized to evaluate the performance.

Due to the different inputs and outputs, two fundamental control methods were categorized to implement this rehabilitation strategy [20]. One is impedance control, in which motion input by the user is measured and force is fed back to the user. The other is admittance control, in which forces exerted by the user are measured and the device will react with the proper displacement to the user. Impedance control requires low inertia and friction and high backdrivability, which can be adapted by commercial haptic devices. However it lacks high forces, high mass and high stiffness and it is difficult to work with complex end effectors [20]. Meanwhile, admittance control devices have enough freedom in the mechanical design, because backlash and tip inertia can be eliminated. Admittance control can just be applied where the contact force between human and device can be accurately obtain. In our study, the ULERD is not backdrivable due to the high ratio gearhead. And it also has multi-DoFs to assist or resist motions of upper limb, so it is difficulty to obtain the accurate contact force between human and device by force sensors due to the difficulties to model the resistance induced by the deformation of human skin and muscle. Therefore, these two methods are not suitable for the ULERD. In this paper, we proposed a novel method to detect the motion of human upper limb with ULERD by offering elastic elements between them, which can be regarded as an elastic extension of human muscles. It is similar to the Serial Elastic Actuator (SEA), which can provide a linear motion detection using serial elastic springs [21]. In this paper, we focused on the resistance generating to human forearm by detecting its rotation motion. Two kinds of experiments were designed to realize the stiffness adjustment of the elbow joint by changed the state passive DoFs locked to the state passive DoFs unlocked. In the experiments, sEMG signals from biceps and triceps muscles were used to do the evaluation of methodology.

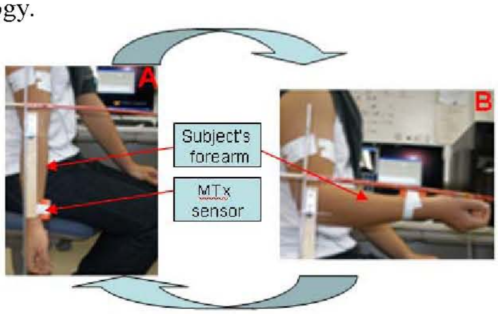


Figure 1 Elbow extension and flexion in experiment

In the next section, we first introduce the ULERD. The control methodology is presented in the Section III. Section IV presents the conducted experiments of stiffness adjustment of the elbow joint and the evaluation of methodology by processing sEMG signals. Finally the paper ends with the discussion and conclusions in Section V and Section VI respectively.

II. OVERVIEW OF ULERD SYSTEM

According to neuro-rehabilitation theory, a rehabilitation robot should achieve the task rehabilitating patients with motor-function impairment with different training strategies. In this paper, we focused on implementing resistance training using the ULERD to generate resistance during elbow flexion and extension as Figure 1 shows. The motion performed in the sagittal plane involved biceps muscle, triceps and other muscles, it is simpler to analyze this motion on the sagittal plane with upper arm relaxed, because the main active muscle is biceps muscle and triceps muscle. The range of motion performed from status A (Figure 1) to status B is about 90 degree that was recorded by the inertia sensor mounted on the wrist. The motion needs to be done three times in one experiment.

A. System description

The system (ULERD) tried to implement active training for upper-limb rehabilitation. A graphical user interface (GUI) was used as the guide to show the predefined task on a computer screen and it also can guide the user to complete the tasks effectively. In the system, an inertia sensor was used to record motion of the forearm and also to generate the different impedance to the forearm. Besides, sEMG signals derived from the relative muscles were utilized to evaluate the efficiency of proposed method.

B. ULERD design

The ULERD can provide passive and active training strategies for patients with motor dysfunction especially upper-limb motor function to recover the elbow and wrist joints. To make it suitable for home rehabilitation, the device was designed light and wearable. The up view of the basic ULERD structure is shown in Figure 2. There are totally three active DoFs consisting of elbow flexion/extension, forearm pronation/supination, and wrist flexion/extension were designed for the elbow and wrist. These three DoFs are all actuated and sensorized. Besides, we also added four passive DoFs, two in the elbow joint and two in the wrist joint [23], in case that variation in the flexion/extension axis, and correlation between the wrist and elbow joint during elbow flexion and extension.

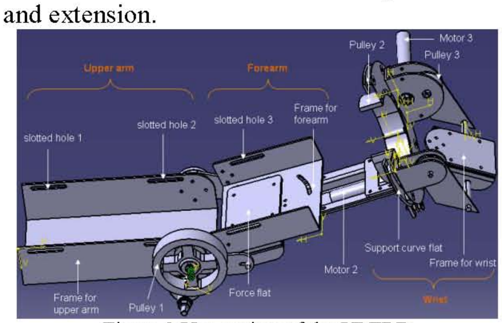


Figure 2 Upper view of the ULERD

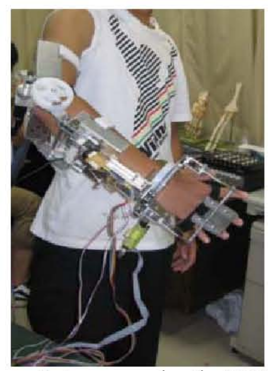


Figure 3 A user wearing the ULERD

In our work, we used high-power density brushless DC motor as the power supply and aluminium material to construct the main frame of the device, in which way the whole weight of the device is 1.3kg. Figure 3 shows a user wearing the ULERD.

C. ULERD kinematics

These passive DoFs were designed to keep ULERD compliant with human upper limbs during the motion. They can also compensate for rotation error of human joints. However, the gravity force on the forearm and wrist parts cannot be completely compensated for, so the device had to be supported by the human forearm to some degree during active training. Given that patients doing active training are able to adjust their upper limbs, passive DoFs are locked during active training, which promoted the resistance stiffness and improves the active rehabilitation effect. In this paper, several contrasting experiments was conducted to show the effect of active training with and without passive DoFs.

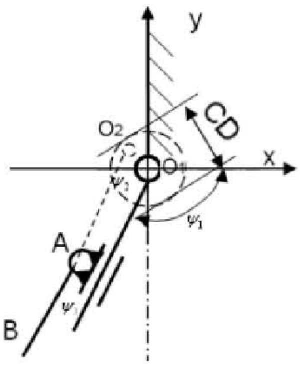


Figure 4 Schematic model of the ULERD elbow joint

Figure 4 shows the schematic model of the ULRED elbow joint with passive DoFs. In this figure, we assume that the upper arm is fixed on y-axis. O_1 is the rotational centre of the device, O_2 is the rotational centre of the user's elbow joint, and the forearm is fixed on AB. A rotational DoF at O_1 is actuated, and two rotational and translational DoFs are the passive DoFs, located at point A. CD is the centre disparity of the elbow joint axis during elbow flexion and extension motion on the sagittal plane. From this figure, we can get the relationship between the human elbow joint and the device as following (Eq. 1 and Eq. 2).

$$\overrightarrow{l_{O_1A}} + \overrightarrow{l_{AO_2}} = \overrightarrow{l_{O_1O2}} \quad (1)$$

$$\psi_1 = \psi_2 + \psi_3 \quad (2)$$

where ψ_1 is the angle between AO_1 and x-axis; ψ_2 is the angle between AO_2 and x-axis, which can be obtained through the inertia sensor; and ψ_3 is the angle between AO_2 and AO_1 ; The detection method is presented below. Eq. 1 is shown as a complex function in Eq. 3,

$$l_{O_1A} \exp(i\psi_1) + l_{AO_2} \exp(i\psi_2) = x + yi \quad (3)$$

And then get Eq. 4 and Eq. 5,

$$l_{O_1A} \cos\psi_1 + l_{AO_2} \cos\psi_2 = x \quad (4)$$

$$l_{O_1A} \sin\psi_1 + l_{AO_2} \sin\psi_2 = y \quad (5)$$

We assume that the elbow joint axis is constant at any moment, so the differential of Eq. 3 can be shown as Eq. 6,

$$l_{O_1A}\omega_1 i \exp(i\psi_1) + V_{O_1AAO_2} \exp(i\psi_1) + l_{AO_2} \exp(i\psi_2) = 0 \quad (6)$$

where $V_{O_1AAO_2}$ is the velocity of AB along AO_1 and can be got as shown below. Eq. 5 is multiplied by $\exp(i\psi_1)$.

$$l_{O_1A}\omega_1 i + V_{O_1AAO_2} + l_{AO_2}\omega_2 \exp(i\psi_2 - i\psi_1) = 0 \quad (7)$$

$$l_{O_1A}\omega_1 = l_{AO_2}\omega_2 \cos(\psi_2 - \psi_1) \quad (8)$$

$$V_{O_1AAO_2} = l_{AO_2}\omega_2 \sin(\psi_2 - \psi_1) \quad (9)$$

Then, the elbow joint position can be calculated by Eqs. 4 to 9.

III. Control Methodology

According to the structure, the ULERD had no backdrivability due to the high ratio gearhead, and also it was difficult to obtain an accurate contact force since it covers human limbs closely. As was mentioned in ref. [24], in which the exoskeleton device can force the motor to rotate over low angles to follow human motion. However the transparency of the system is low. In our study, elastic components were used to detect human motion in a HMI system in which the device has no backdrivability. Similar to a serial elastic actuator [25], in which linear elastic springs were used to detect motion of the load, this study used elastic materials to detect the relative rotation of the user's forearm. By considering the proposed methods, variable resistance using a spring model, damper mode, or integration mode can be provided to the user's upper forearm. The experiments showed in part IV focused on the elbow joint using the proposed method.

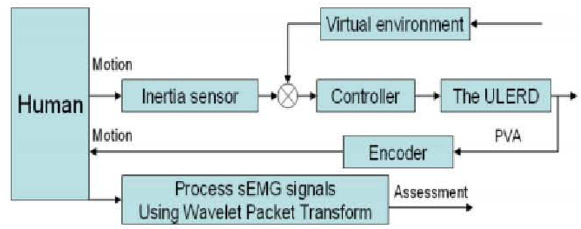


Figure 5 Control scheme for the system

The scheme for control system is shown in Figure 5. An inertia sensor was used to obtain human limb motion information, including position, velocity, and acceleration. These parameters were calculated depending on the virtual motion and then were sent to motor controllers as input which were driven in position with a closed-loop velocity control and an inertia sensor and encoders using a proportional–integral–derivative (PID) control algorithm. Also sEMG signals from the relative muscles during the elbow motion were used to evaluate the effect of the proposed method.

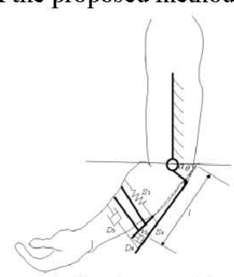


Figure 6 Schematic model of resistance with passive DoFs locked

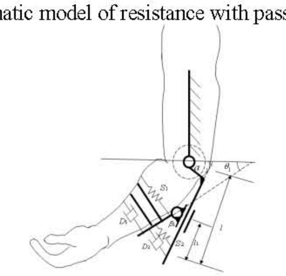


Figure 7 Schematic model of resistance with passive DoFs unlocked

Figure 6 shows the schematic model of resistance with passive DoFs locked, while Figure 7 states passive DoFs unlocked in contrast. In the state passive DoFs unlocked, spring and dampers models are used, the resistance effect of dampers was generated by adjusting the elastic belts, though no damper components were in it. By changing the state of the passive DoFs, the stiffness adjustment of the device is realized during the elbow flexion and extension.

The elastic elements used in the device, as figure 8 shows. These springs not only can change the stiffness of the system but to help to obtain the force exerted on the forearm.

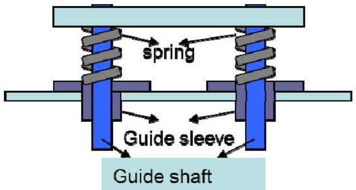


Figure 8 Structure of the elastic element

A. Control methodology

- Flexion motion

During flexion motion, the force exerted on the user's forearm can be obtained by spring S_1 and damper D_1 using Eq. 10,

$$F_1 = k_1(\theta - \theta_1)l + c\dot{\theta} \tag{10}$$

where k_1 is the coefficient of spring S_1; c_1 is the coefficient of damper D_1; θ detected by an inertia sensor represents the angle between the forearm and horizontal plane; Then θ_1 represents the angle of the forearm frame and horizontal plane; $\dot{\theta}$ represents the velocity of forearm angle; and F_1 is the virtual resistance to the user arm. Thus $F_1 - c\dot{\theta}$ represents the actual resistance to the user arm and l represents the length between the elastic belt and the elbow axis. Then the angle θ_1 can be get from Eq. 10.

According to figure 7, the rotational angle of the elbow joint can be obtained as the Eq.11.

$$\alpha - \beta = \theta_1 \tag{11}$$

Where α represents the angle of the device elbow joint and β represents the rotational angle of passive joint detected by a potentiometer. The motor can be controlled by α as Eq.12 shows,

$$\alpha = \beta + \theta - \frac{F_1 - c\dot{\theta}}{k_1 l} \tag{12}$$

When the passive DoFs were locked, then the calculating method would be changed. The force exerted on the forearm with respect to spring S3 and damper D3 can be obtained by Eq.13.

$$F_3 = k_1(\theta + \alpha - \frac{\pi}{2})l + c_1\dot{\theta} \tag{13}$$

Where F_3 is the desired virtual force during the elbow motion, finally the same as above, α can be obtained by the Eq.13.

- Extension motion.

During extension motion, the force exerted on the user's forearm can be calculated with respect to spring S_2 and damper D_2,

$$F_2 = k_2(\beta_1 - \beta)l_1 + c_2\dot{\theta} \tag{14}$$

Where k_2 is the coefficient of spring S_2, c_2 is the coefficient of damper D_2, β_1 represents the initial angle of the passive rotated joint, and l_1 represents the length between the elastic belt and the passive joint axis.

The difference from the flexion motion, in extension motion, forearm and the frame of the device are so closely that θ equals θ_1, then α can be obtained as Eq.15 shows.

$$\alpha = \frac{F_2 - c_2\dot{\theta}}{k_2 l_1} - \beta_1 - \theta \tag{15}$$

Where $F_2 - c_2\dot{\theta}$ is the real resistance generated to the limb and the target of control is finding the θ using the closed-loop position control method to meet the resistance.

When the passive DoFs were locked, the force analysis during the motion changed as follows.

$$F_4 = k_2(\theta + \alpha - \frac{\pi}{2})l + c_2\dot{\theta} \tag{16}$$

As the same as analysed above, α can also be obtained from the Eq.16.

IV. Experiments and Results

A. Guide in a virtual environment

In the experiment conducted below, we constructed a three-dimensional interface based on OpenGL, in which two virtual upper limbs were created as figure 9 shows. One moves at a programmable speed within the range of motion called tracked arm, the other showed the motion of the user's limb called operated arm. The experiment worked like this. The user was asked to manipulate the ULERD to make the operated arm in the virtual environment follow the tracked arm during elbow flexion and extension, in which the virtual force was programmed. Then a certain resistance was generated and exerted to the user limb.

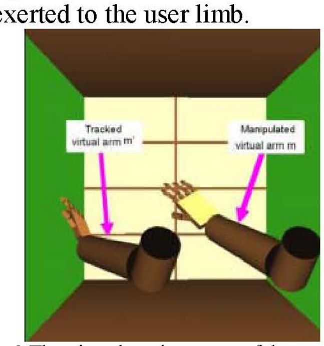


Figure 9 The virtual environment of the experiment

B. sEMG signal acquisition and processing

This experiment also utilized sEMG signal to evaluate the effect of the proposed method. sEMG is now widely used to estimate muscle torque and to drive exoskeletal devices since it can deeply reflect muscle activation [27]–[29].

During the elbow flexion and extension with forearm relaxed, we just assumed only the biceps and triceps muscles are activated in which way only two channels EMG signals were used in the experiment. We did the signal acquisition using 12-mm-diameter bipolar surface electrodes located 18 mm apart on the biceps and triceps muscles respectively. The reference electrode was attached to where no muscles was used as the ground signal. This work was done by a commercial sEMG acquisition and filter device (Osaka Electronic Device Ltd., Osaka, Japan) at a sampling rate of 1000 Hz through an AD sampling board (PCI3165; Interface Co., Chiba, Japan). Before the data acquisition, the skin of subject should be shaved and cleaned with an alcohol swab to ensure good contact.

Then we implemented the data filtering using wavelet transform packet (WTP) with Matlab software, since WTP was commonly used to do feature extraction. We took Daubechies 2 as the mother wavelet to do the decomposition, and the detail coefficients at the fourth level were utilized to describe the EMG signal according to refs. [30]–[32]. Then they were integrated with 100 samples as the features.

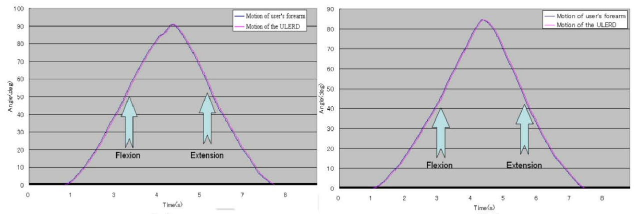
Figure 10 Experimental setup for sEMG signal acquisition

C. *Experiments and results*

One healthy subject was invited in this experiment who was asked to do the elbow flexion and extension motion using ULERD. Two sets experiments were designed with passive DoFs locked and with passive DoFs unlocked. In the state of unlocked, the displacement of the forearm and the frame of the ULERD were shown according to θ and $\alpha-\beta_1$ while in the state of locked they were $\theta-\pi/2$ and α. In each set of experiment, we designed different parameters to generating different resistance. For example, we can set θ equals $\alpha-\beta_1$ or $\theta-\pi/2$ equals α to perform the elbow motion with no resistance; We can also set a parameter k in the equation $k=\theta-\pi/2-\alpha$ or $k=\theta-\alpha+\beta_1$ to represent to resistance added to the limb, the higher values of k means higher resistance added, so that k equals zero means no resistance was added is also included in. The coefficients c_1 and c_2 of the damper were set to 1.0 Ns/rad according to the tremble in velocity.

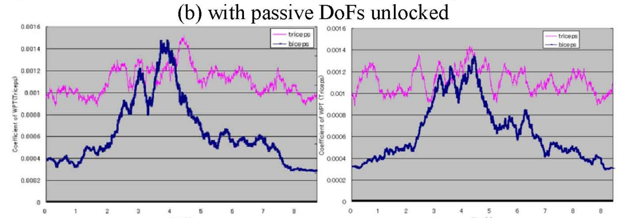
Figure 11 show results of the experiments k equals zero. They represent the angular record of the forearm and the ULERD during the motion presented as blue and red curve respectively. They seem to be all the same in both states (a) and (b).

However in figure 12, which show processed EMG signals from the triceps and biceps muscles presented as blue and red curve respectively, we can get more information. The shape of the two figures is almost the same, they all describe the elbow motion since EMG signals are deeply related to the muscle activation. The values at about the fourth second are higher in both figures, that's because the forearm was moving to the horizontal plane, and the biceps were activated. The values of triceps shown as red curve in (a) was almost the same as that in (b), indicating similar triceps activation in these two performances, meanwhile, values from the biceps in (a) was lower than that in (b), which was caused by some gravity compensation by the forearm frame of the device with the passive DoFs locked, proved to us that the stiffness of the system was increased at the same time.



(a) (b)

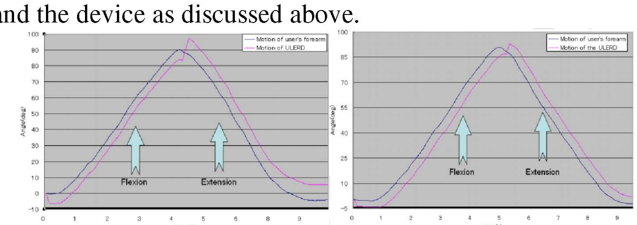
Figure 11 Motion record with no resistance. (a) with passive DoFs locked (b) with passive DoFs unlocked



(a) (b)

Figure 12 sEMG signals with no resistance. (a) with passive DoFs locked (b) with passive DoFs unlocked

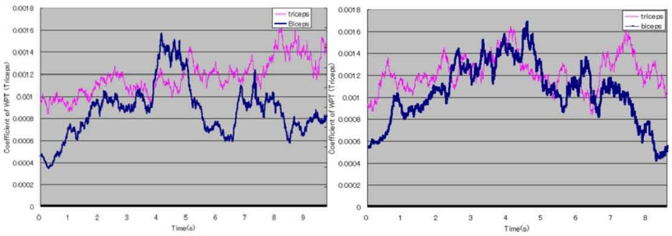
Then we tried to set the nonzero value of k to find out the effect variation of the system due to the increasing resistance on the limb. Figure 13 shows the motion record of the forearm and the device as discussed above.



(a) (b)

Figure 13 Motion record with nonzero resistance. (a) with passive DoFs locked (b) with passive DoFs unlocked

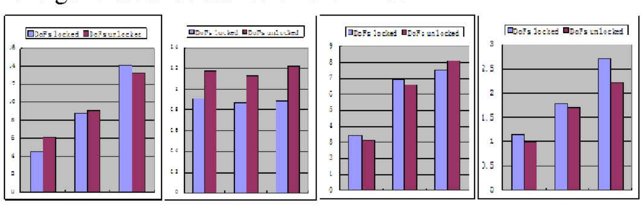
In figure 13, resistance was provided to the user's forearm by setting the value of k to be nonzero one to present the relative displacement between the user's forearm and the ULERD. In both (a) and (b), a bulge occurred in the motion trajectory because the displacement between the user's forearm and the ULERD changed, in which flexion motion changed to extension motion. The misalignment provides us the information that resistance had been generated on the limb. By comparing with figure (a) and (b), we can also find out the resistance provided in state with passive DoFs unlocked was smoother than that provided in state with passive DoFs locked because the misalignment could be corrected due to the elastic elements.



(a) (b)

Figure 14 sEMG signals with nonzero resistance. (a) with passive DoFs locked(b) with passive DoFs unlocked

Figure 14 shows the processed sEMG signals from the biceps muscle and triceps muscle as disscussed above. This time nonzero resistance was added on the user's limb,
The magnitude of the WPT coefficients of the sEMG signals derived from the biceps in figure 14 was higher than that in figure 12 , particularly during flexion motion. In contrast, the magnitude of the WPT coefficients of the sEMG signals from the triceps in figure 14 was higher than that in figure 12 during extension motion, which indicates that the resistance is put on the forearm during extension. This can show us the variation of the muscle during the motion and the performance of the generated resistance on the limb.



(a) (b) (c) (d)

Figure 15 Mean WPT coefficients from processing the biceps and triceps sEMG signals during the elbow motion with passive DoFs locked and unlocked. (a) Biceps muscle in flexion (b) Triceps muscle in flexion(c) Biceps muscle in extension (d) Triceps muscle in extension

Figure 15 shows the mean WPT coefficients from processing the biceps and triceps sEMG signals during the elbow motion. (a) presents the biceps muscle in flexion motion, (b) presents the triceps muscle in flexion motion, (c) presents the biceps muscle in extension motion, (d) presents the triceps muscle in extension motion. In each figure, red color bar stands for the state with passive DoFs unlocked, the other stands for the state DoFs locked, they showed us the variation of the activities of the muscle by the increase of the value k from zero to nonzero. From (a) and (b), we can get that during the flexion motion, only the activity of the biceps muscle soars by the increase of k ,activity of the triceps muscle nearly keep the same. In the state of DoFs locked, the increase seems sharply than that of DoFs unlocked, which proved the evidence that the elastic elements could correct the misalignment due to the variation of the device's stiffness.

From (c) and (d), we can get that during the extension motion, both the biceps muscle and triceps muscle are all activated, since they all soar by the increase of k .They can also prove the resistance provided in state with passive DoFs unlocked was smoother than that provided in state with passive DoFs locked. The different is, by the increase of k , the activity of triceps muscle increased sharply than that of biceps muscle which nearly keep the same when k has a high value. So we can draw the conclusion that when the k is small, the resistance was mainly added on the biceps muscle, while when k is large enough, the resistance was mainly added on the triceps muscle. This may help us to design effective resistance training strategies for the upper-limb rehabilitation using an exoskeleton device.

V. Conclusions

This paper proposed a method that detects the motion of the human forearm instead of the device for an upper-limb exoskeleton rehabilitation device for home rehabilitation which was lack of backdrivability and accurate detection of contact force between the human and the device. The structure of the passive DoFs unlocked was designed to correct misalignment between the human and the device to make it more comfortable to the user; However, this may reduce stiffness of the device that active training could not be implemented completely according to the experimental results, particularly with the high resistance required, but in which way the resistance provided was smother than that provided in state with passive DoFs locked. Contrast experimental results indicated that the proposed method of exerting different resistance implemented by changing the value of k . During the elbow motion, the biceps muscle and triceps muscle activated to different degree due to the resistance generated on the limb, from mean WPT coefficients from processing the biceps and triceps sEMG signals shown in figure 15, we could come up with more efficient method to implement the resistance training for the exoskeleton rehabilitation. This method was proved to be effective to generate variable resistance for active training by using the ULERD and will be further tested for home rehabilitation in future work.

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