Muscle Force Estimation Method with Surface EMG for a Lower Extremities Rehabilitation Device

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Abstract— **This paper presents a new wearable lower extremities assistive robotic device that aims at providing assistive torque for stroke patients during rehabilitation process. The device specifically provides the assistive torque by detecting the user's intention using surface electromyography (EMG) signals with the force/torque estimation method based on continuous wavelet transform (CWT). The general hardware design of the current rehabilitation prototype was developed. Experiments were conducted to collect hamstring and quadriceps muscles EMG signals from 10 healthy subjects. Data analysis was carried out to evaluate the feasibility of the proposed human force/torque estimation algorithm. The force/torque estimation results show high implementation feasibility for the assistive device. Online tests were also carried out with the assistive device using the EMG signal to command motors. The output estimation force, hip and knee joint positions were obtained from the real-time implementation.**

Keywords—Robotic assistive device, lower extremities rehabilitation, electromyography (EMG), continuous wavelet transform (CWT), muscle force estimation.

I. Introduction

Stroke has become a leading cause of chronic and serious disabilities in recent years. Neurological impairment after stroke frequently leads to hemiparesis and one-side motor impairment of the body, which affects the patient's ability to perform daily activities. Research studies have found repetitive training exercises of the affected limb could enhance and recover the motor function [1]. High intensity, task-oriented rehabilitation training has shown to enhance the walking ability of patients after stroke, particularly for those with moderate walking deficits [2]. Robotic exoskeletons and assistive devices have been widely developed for a variety of applications. Devices such as the AutoAmbulator, GaitTrainer, LOPES [3] and ALEX [4] are designed as automated lower extremities gait training on a treadmill. The Lokomat [5] is designed for stroke patients gait training with an advanced body weight support system, a robotic gait orthosis and a treadmill. It adjusts the shape of the desired stepping trajectory based on the participant's interaction forces, as well as the robot impedance. Most of the rehabilitation devices move the patient's legs through a fixed gait trajectory and there is no cycle-to-cycle variation in the kinematics and bio-signal feedback. Hybrid Assistive Limb (HAL) [6] is a wearable robot designed for assisting the elderly and stroke patients. The latest HAL exoskeleton is controlled by surface electromyography (EMG) signals to trigger the movement and drive the motor to assist movement-deficient elderly and disabled persons. There are many other lower extremity assistive devices designed for aiding people, such as RoboKnee [7] and Quasi-Passive Exoskeleton [8]. For these devices, multiple actuation systems and human-machine interfaces were applied. However, due to limitations in price, size and portability, most of these devices are not suitable for casual indoor or home usage. Therefore, it would be advantageous to have a portable rehabilitation device give the users walking assistance for both hospital and home use.

The EMG signal [9] is one of the most informative sources for human intention suited for rehabilitation devices. Using EMG signals to estimate user's intention is one of the most effective and user-friendly ways for the control of the assistive devices. Therefore, the measurement of the forces applied to a joint and prediction of the force generated by muscles are essential for the development of rehabilitation devices. An EMG signal is the action potential generated in a muscle as the command signal from the motion control system of a person is transmitted to the muscle through the motor nerves. Before muscles contract, EMG signals will be generated to command the action. Hence, EMG signals can be used as a predictor of force exerted by muscles.

EMG signals for predicting human limb movement and the amount of force required to accomplish a task have been widely researched in recent decades [10]. The features of the EMG signal such as averaged rectified value (ARV), low-pass filters and root mean square (RMS) are commonly used to estimate force/torque. Lubecki et al [11] used filters and RMS methods to develop the EMG-force relationship and force estimator. Results showed that the signal processing was done with a small time delay of less than 60 ms. Some force estimation studies consider the system electromechanical delay or obtain the estimated force from EMG signals before the muscle contracts. In assistive devices area, not many studies utilized the EMG signal to detect the intention of the users since the analysis of the EMG signals in human body introduces much complexity to the control system. However, this approach appears to be the simplest solution for purely intuitive human-machine interfaces.

This paper first presents the hardware design of a new wearable lower extremity rehabilitation device prototype. Experiments were conducted to collect the off-line hamstring and quadriceps EMG signals from 10 healthy subjects (6 males and 4 females). Continuous wavelet transform (CWT) was used to extract the time-frequency features of EMG signals. The actual applied forces from the subjects were measured as a reference to compare with the estimated force. EMG signals analysis was carried out to explore the feasibility of the proposed human force/torque estimation algorithm. Online tests were also carried out on the rehabilitation device.

II. METHODS

A. Rehabilitation Device Prototype

The lower extremities assistive device for rehabilitation was designed to aid in the flexion and extension motion of the user's hip and knee joints (Fig. 1). This device consists of a lightweight adjustable anthropomorphic frame based on the anthropometrical data provided in [12], with actuator modules attached at the joints. Orthotic cuffs are used as the attachment interface between the device frame and the user. Each powerful actuator module could deliver up to 35 Nm torque and is powered by a DC motor attached to a harmonic drive at a 50:1 gear ratio. An optical incremental encoder is also equipped at the pre-reduction stage of each actuator module to measure the joint angle. To ensure the safety of the user, the range of motion of each joint is limited to be slightly smaller than the normal range of motion of a human.

A reconfigurable embedded control and acquisition system which consists of a real-time processor, reconfigurable field-programmable gate array (FPGA), analog and digital I/O is used for the control of the device. Each actuator module is controlled by a digital servo driver. Controller area network (CAN bus) communication at 1 Mbits/s is implemented between the controllers.

B. Subjects

Six male and four female healthy subjects (age 26.3±1.8 years, weight 60.2±9.2 kg and height 168.4±7.5 cm) voluntarily participated in this study. Each subject agreed and signed the written informed consent documents before participating in the experiments. They were informed about the experimental procedures. All the subjects were healthy with no known neurological disorders or musculoskeletal problems. The experiments were approved by the local institutional review board.

C. Surface EMG and Force Measurements

Surface EMG signals were collected from the quadriceps femoris and hamstring muscles. EMG signals were recorded using self-adhesive Ag/AgCl surface electrodes. All electrodes pairs were placed parallel to the general direction of muscle fibers on the selected muscle groups. Electrodes pairs were placed with the distance between the electrode's centers of 20 mm. And the electrodes placement and locations onto the target muscles according to SENIAM guidelines. To reduce the electrical impedance between the skin and electrodes, skin preparation (removal of excess hair and cleaning of the skin with alcohol) was undertaken before electrodes were attached to the skin. Contraction tests were carried out to make sure there was good contact between the electrodes and skin. EMG signals were pre-amplified at the electrode site and the common mode rejection ratio of the pre-amplifier was over 95 dB. The recorded signal was subsequently stored in a computer for off-line analysis.

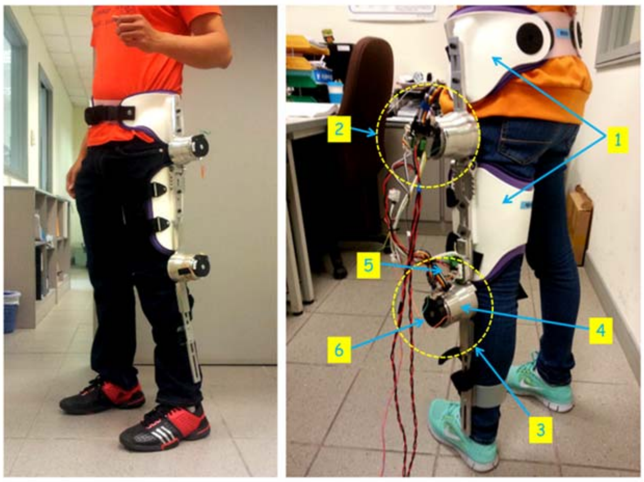


Fig.1 Lower extremities rehabilitation device prototype with users. 1: Orthotic cuffs; 2: Hip joint actuator module; 3: Knee joint actuator module; 4: DC motor and harmonic drive housing; 5: Digial servo drive; 6: Incremental encoder

A force measurement setup using bidirectional strain gauge was designed to measure the force exerted by lower limbs. Force signals from the strain gauge was amplified with a strain gauge amplifier. The force and voltage relationship of the force measurement setup was calibrated using a digital force gauge (IMADA, DS2-50N) before the experiments were conducted. The measured force was also used as a reference to validate the feasibility of the proposed force estimation method.

D. Experimental Protocol

Subjects sat comfortably in front of the force measurement setup and they were asked to move their dominant legs by performing the knee extension/flexion to pull or push the setup handles. To help the subjects familiarize with the setup and the experimental tasks, warm-up exercises were performed. The measured force from force sensor was collected at the same time as the contraction was performed. Graphs depicting the target force, actual applied force and EMG signals were displayed real-time on a computer screen facing the subjects to provide a visual biofeedback while they performed their muscle contractions. Fig. 2 shows the experimental setup used to measure the force exerted by muscles.

The EMG signals were recorded from the two muscle groups separately. For each subject, four trials were performed. In the initial two trials, each subject was asked to perform the knee flexion or extension of the two muscle groups from maximum voluntary contraction (MVC) to a relaxed state with a slowly ramp down contraction. In the following two trials, a target trajectory of force amplitude in the shape of a dynamic half-sinusoidal was displayed. The subjects exerted muscle contraction forces in accordance to the trajectory by performing knee joint flexion or extension. EMG signals were recorded at a sampling rate of 10 KHz using a USB data acquisition (DAQ) device (National Instruments). The collected signals were used for off-line analysis by down sampling to 5000 Hz in MATLAB for further signal processing. A sample of the raw EMG signal recorded from quadriceps by performing knee extension is shown in Fig. 3.

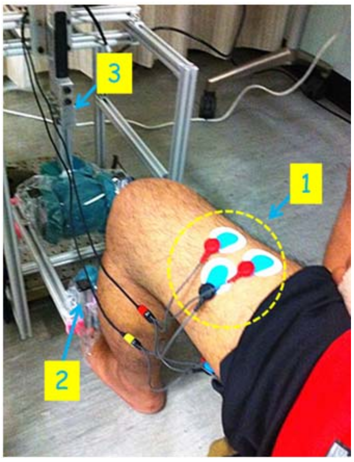


Fig.2 Experiment setup. 1: surface EMG electrodes; 2: handle for legs experiments; 3:force sensor.

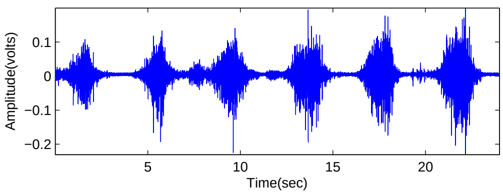


Fig. 3. Sample of the recorded raw EMG signal from one trial (Quadriceps: knee extension).

E. Data Analysis for Force Estimation

When muscles contract under a force-varying force, the EMG signals cannot be assumed to be stationary, which implies that the traditional signal processing approaches may not be suitable. Under such circumstance, time-frequency analysis is more appropriate as it would provide direct information about the frequency components occurring at any given time. In the time-frequency analysis methods, mean frequency (MF) of the power spectral density is one of the most commonly used characteristics of EMG signals [9, 13, 14]. CWT was applied to obtain the MF of the EMG signals. CWT is a time-scale representation which is suitable for analyzing non-stationary and time-varying signal. Given the input signal $s(t)$, CWT of the signal $s(t)$ is defined as

$$W_s(a,\tau) = \int_{-\infty}^{\infty} s(t)\, \varphi_{a,\tau}^{*}(t)dt \quad (1)$$

where a represents the scale parameter, τ represents the translation parameter (time shifting), $\varphi_{a,\tau}^{*}(t)$ could be calculated by scaling the mother wavelet $\varphi(t)$ at time τ and scale a [15, 16],

$$\varphi_{a,\tau}(t) = \frac{1}{\sqrt{a}}\varphi\left(\frac{t-\tau}{a}\right) \quad (2)$$

The square of the absolute value of the CWT value $E(\omega) = |W_s(a,\tau)|^2$ is called Scalogram and it represents the energy distribution of the EMG signal over the entire time-scale plane. The Scalogram is a two dimensional $(i \times j)$ matrix of squared wavelet coefficients. The wavelet coefficients consist of i columns (i is the number of the input signal sample points) and j rows (j is the length of the wavelet scale parameters). The relationship between wavelet scale and frequency is defined as

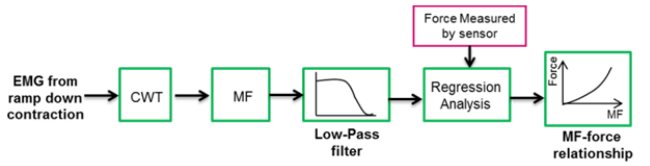
$$f_a = \frac{f_0}{a} f_s \quad (3)$$

where a is the scale, f_s is the sampling frequency of the EMG signal, f_0 is the center frequency of the mother wavelet, f_a is the pseudo-frequency (Hz) corresponding to wavelet scale a. In MATLAB implementation, "Morlet" mother wavelet with a wavelet scale length of 196 was selected to calculate the Scalogram. By using the scalogram, the MF representing the EMG signal frequency characteristics, which can be defined as the average frequency of the signal power spectrum,

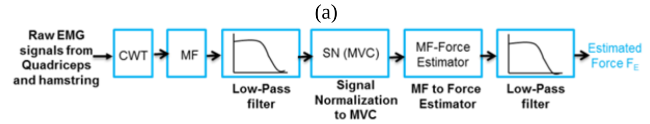
$$MF = \frac{\int_0^{\infty} \omega E(\omega)d\omega}{\int_0^{\infty} E(\omega)d\omega} \quad (4)$$

where ω is the frequency variable.

Fig. 4 is the signal flow diagram for the proposed CWT-based force estimation method. Fig. 4 (a) shows the procedures to derive the polynomial describing the MF-force relationship. EMG signals from each subject under ramp down muscle contractions were used. First, to smooth the MF signal, a 4th order Bessel filter with the cut-off frequency at 5Hz was used. Linear regression analysis was employed to establish the polynomials describing the relationship between filtered MF signal and the measured force.



(a)



(b)

Fig. 4. Signal flow diagram. (a) MF-Force relationship establishment method; (b) Proposed CWT-based force estimation method.

In the proposed force/torque estimation method (Fig.4 (b)), a 4th order low-pass Bessel filter with 5Hz cut-off frequency was applied to smoothen the MF signal. Afterwards, the filtered MF signal was normalized to the maximum mean frequency of the contraction trial. This normalization procedure reduces the variability in signal amplitude between subjects due to differences such as muscle length, electrodes locations and fiber conduction velocity. The estimated force is obtained by feeding the normalized signal to the MF-force relationship polynomial estimator. At this stage, the estimated force is not very smooth, and the noise should be reduced for a higher estimation accuracy. This problem is addressed by using a Bessel 4th order low-pass filter with 9 Hz cut-off frequency for post-processing, even though it would induce some time lag. The output signals after low-pass filtering are the direct estimation of force/torque produced by the measured muscle groups.

F. Real-time Implementation

The proposed CWT-based force estimation algorithm was implemented to the real-time embedded controller (National Instruments, NI sbRIO-9612) with the lower extremities rehabilitation device for validation and to control the knee joint. Subjects performed the real-time experiments using the EMG signals from quadriceps femoris muscles. To make the subjects familiarize with the device and the experimental tasks, warm-up exercises were carried out first. This also helped these inexperienced subjects to perform independent movement and proper operation of the device. To confirm the effects of assistance as physically sensed by its users, repetitive squatting and sit-stand motion experiments were conducted by mounting the device on subjects. The subjects were asked to perform the two legged squatting by knee extension and flexion with around 6 s per cycle. In another trial, 6 cycles of the repetitive sit-stand was performed by subjects in 30 s. Fig. 5 illustrates the signal flow for EMG signal controlling the knee joint. Raw EMG signals were acquired by the analog input at the sampling frequency of 10 KHz. The estimated normalized force was amplified by a proper selected gain, and transmitted as a desired assistive torque via CAN bus to the digital servo driver to actuate the motor. The transmission speed of the CAN bus was set to 1 Mbits/s. Raw EMG signals, the normalized estimated force, hip and knee joint position data were measured and displayed on the LabView user interface for online monitoring and data recording.

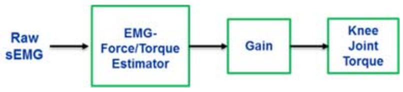


Fig.5. Signal flow of EMG control structure

III. Results

A. MF-Force Relationship

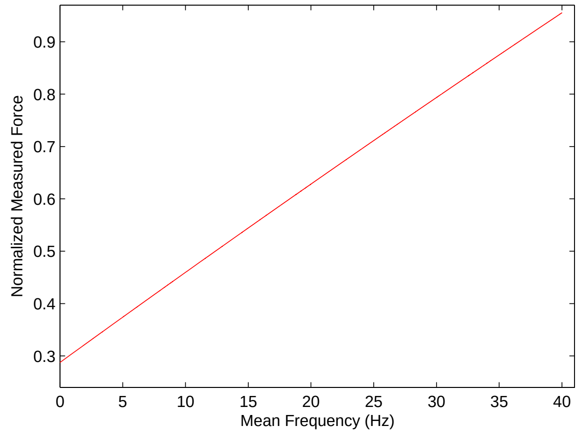
For the two measured muscle groups, MF-force polynomial estimators were obtained from each subject. The best polynomial estimator selected was the one that gave the highest R^2 values and lowest root mean square error (RMSE). Fig. 6 illustrates the MF-force relationship curves for quadriceps femoris and hamstring muscles. Two nonlinear relationships between MF and measured force were found for the hamstring and quadriceps muscles. The estimators for quadriceps femoris and hamstring were 3rd order polynomial with different coefficients,

$$Y=m_3x^3+m_2x^2+m_1x \quad (5)$$

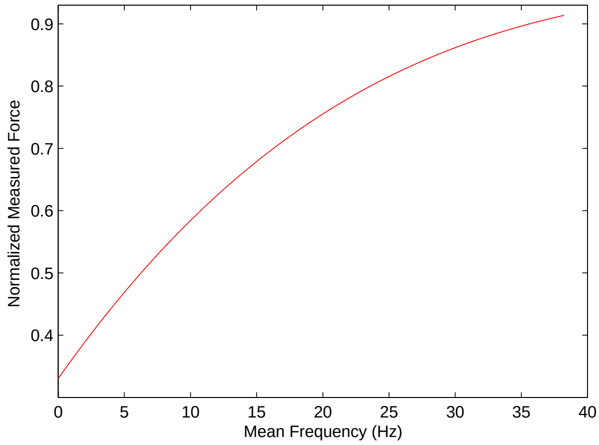
where m_1=7.174, m_2=-1195, m_1=71350 for hamstring, and m_1=1.607, m_2=-503.8, m_1=65620 for quadriceps femoris. In equation (5), x is the filtered MF signal and the output Y of the polynomial is the estimated force.

B. Muscle Force Estimation

Fig. 7 shows the preliminary results of the measured force and the estimated force from hamstring for one single contraction (subject 10). The green solid line indicates the measured force, while the blue dash-dot line shows the predicted force by the proposed CWT-based method. The estimated force and measured force amplitudes are all normalized to the maximum force value for avoiding the variability induced from different subjects and different muscles during muscle contractions. Fig. 8 depicts the estimated force and measured force for the two muscles under knee flexion/extension performed by subject 8. The negative force values measured are induced by the muscle adjustment of the subjects coupled with the sensitive nature of the bidirectional force sensor used.



(a)



(b)

Fig. 6. Example of regression fit of the polynomial estimators, non-linear relationship between MF and the measured force. (a) Quadriceps: knee extension; (b) Hamstring: knee flexion.

Since the EMG signals detect the electrical potential generated by muscle cells when these cells are electrically or neurologically activated, the estimated forces should theoretically lead the measured force by a few milliseconds with proper signal processing. The leading time, the root mean square (RMS) errors and the cross-correlation coefficients between the estimated force and the measured force were obtained to evaluate the efficiency of the proposed method. The leading time, RMS errors and correlation coefficients of the ten subjects are shown in Table 1. The average leading time for the quadriceps femoris and hamstring are 80.62±26.3 ms and 61.7±19.5 ms respectively. The RMS errors are very low with 0.13±0.04 and 0.25±0.03 for the quadriceps and hamstring respectively. High correlation coefficients were found for the estimated force and the measured force, 0.94±0.03 for the quadriceps and 0.97±0.01 for the hamstring respectively.

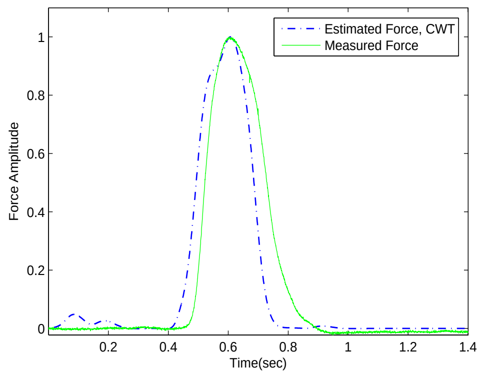
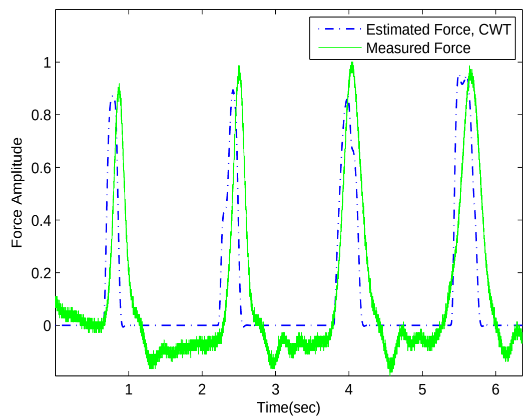
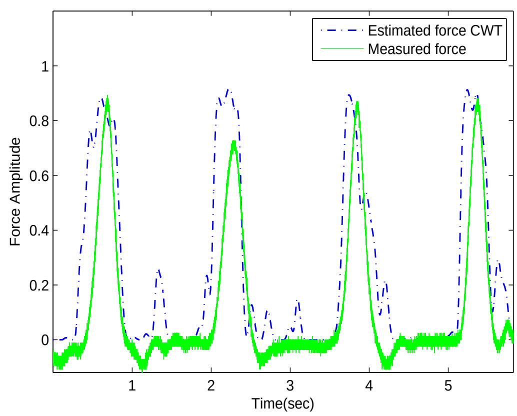


Fig. 7. Force estimation results using CWT-based methods for subject 10. The green solid line indicates the measured force, while the blue dash-dot line shows the predicted force by the CWT-based method.(Force amplitude is normalized to 1).



(a)



(b)

Fig. 8. Force estimation results (subject 8). The green solid line indicates the measured force, the blue dash-dot line shows the predicted force by the CWT-based method. (a) Quadriceps (knee extension); (b) Hamstring (knee flexion).

TABLE I. CWT-BASED FORCE ESTIMATION RESULTS (AVERAGE LEADING TIME , RMS ERROR AND CORRELATION COEFFICIENTS OF EACH SUBJECT)

Subjects	*Quadriceps femoris*			*Hamstring*		
	Leading Time (ms)	RMS Error	Correlation Coefficients	Leading Time (ms)	RMS Error	Correlation Coefficients
s1	90.8	0.0957	0.9710	96.4	0.2118	0.9320
s2	99.4	0.0736	0.9704	25.8	0.2867	0.9808
s3	63.8	0.0837	0.9698	42.4	0.2548	0.9830
s4	90.4	0.1328	0.9464	74.4	0.2408	0.9831
s5	104.6	0.1428	0.9431	51.6	0.1959	0.9799
s6	18.6	0.1302	0.9364	51.8	0.2396	0.9765
s7	107.6	0.0930	0.9727	68.8	0.2920	0.9332
s8	88.0	0.1955	0.9061	66.0	0.2876	0.9581
s9	67.2	0.1878	0.9021	69.0	0.3159	0.9638
s10	75.8	0.2110	0.8842	70.4	0.2592	0.9696

C. *Real-Time Implementation on Rehabilitation Device*

During the real-time implementation, some signal processing parameters of the proposed algorithm were modified to achieve good muscle force estimation results. The recorded raw EMG signals were down sampled to 2 KHz for signal processing. The cut-off frequency of the low-pass filter implemented on MF was reduced to be 3Hz and no more low-pass filter was implemented on the estimated force. To ensure the safety of the subjects, the selected gain was 3 and the peak torque was set for the motor to be 25Nm. Fig.9 and Fig.10 show the online data during repetitive squatting and sit-stand. The knee joint is controlled by the estimated force/torque and the positions change following the estimated force/torque. The hip joint positions were also recorded by encoder. For the sit-stand motion, the knee and hip joint angles reach the designed joint limit when the subjects sit down. From the feedback of all subjects, they felt that there was significant assistance from the rehabilitation device while performing the given tasks as the device was able to provide assistive torque according to the subjects' intention.

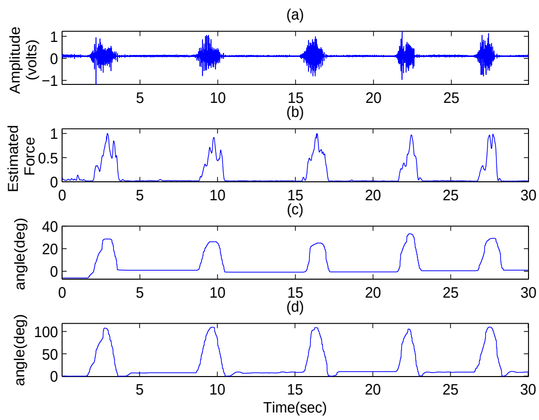


Fig.9. Muscle force estimation method real-time implementation on rehabilitation device during repetitive squatting. (a) Raw EMG signal from quadriceps femoris muscles; (b) Estimated muscle force/torque; (c) Hip joint angle; (d) Knee joint angle

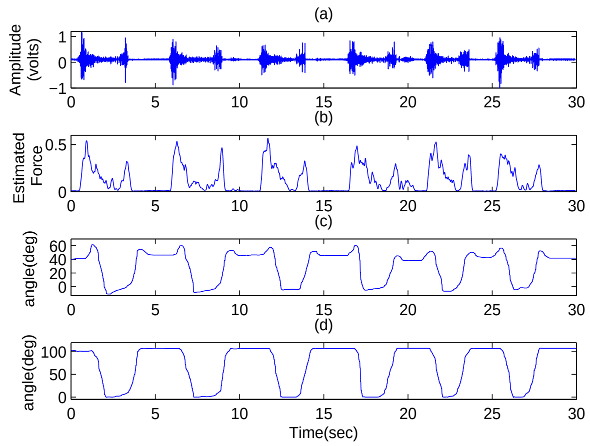


Fig.10. Muscle force estimation method real-time implementation on rehabilitation device during repetitive sit-stand. (a) Raw EMG signal from quadriceps femoris muscles; (b) Estimated muscle force/torque; (c) Hip joint angle; (d) Knee joint angle

IV. CONCLUSION AND DISCUSSION

In this study, a new wearable lower extremity assistive device for rehabilitation was developed to provide assistive torque by detecting the user's intention. EMG signals were recorded from subjects' quadriceps femoris and hamstring for off-line processing. The human intention and muscle force/torque were estimated with the proposed CWT-based algorithm. The force/torque estimation results show high implementation feasibility on the rehabilitation device. Real-time implementation was also carried out on the rehabilitation device. The main advantage of using EMG signals over other non-bio-feedback methods for human machine interface is the real-time intuitive human intention detection. It also ensures the intuitive and effortless control from the user's perspective.

In this proposed force estimation method, CWT gives an accurate calculation of MF. Moreover, CWT is the most computational and storage efficient method among other time-frequency methods as it does not generate redundant solutions which is a common problem in other methods [13]. Typically, most of the relationships were developed based on the time domain features of EMG signals, while the time-frequency analysis characteristics were relatively seldom considered. In this work, the non-linear relationships between MF and muscle forces were obtained, which implies that the time-frequency features of EMG signal allows predicting the muscle force. However, human muscles can be fatigued even with external assistance and the performance of the human should be degraded significantly. For future development, a muscle fatigue detection algorithm will be developed and implemented on the robotics assistive device. Further testing on more subjects is also essential to improve the current device.

ACKNOWLEDGMENT

This work is under the project of novel rehabilitation device for lower extremities. We acknowledge the financial support from the Singapore Ministry of Education (MOE) Academic Research Fund (AcRF) (Grant No.: R-265-000-419-112). The authors would like to thank the NUS control and mechatronics lab and all the participants in the experiments conducted.

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